Temporal dynamics of resilience in the palladium supply chain

A data analytics approach

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Master thesis submitted to Delft University of Technology in partial fulfilment of the requirements for the degree of

Master of Science
in *Engineering and Policy Analysis*

Faculty of Technology, Policy and Management
To be defended publicly on February 19th, 2024

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Project Duration:	September, 2023 - February, 2024
Programme:	Engineering & Policy Analysis
Faculty:	Technology, Policy and Management, Delft University of Technology

TUDelft

Acknowledgements

This document marks the end of my time as a student in Engineering & Policy Analysis at Delft University of Technology. As an EPA student, I have learned a lot about both the technical aspects of modelling and data analytics as well as the implications and challenges of applying them in an uncertain, multi-actor context. The thesis process has been a very educational experience, in which I learned more about critical raw materials, supply chain resilience, and the process of doing research. However, as the cliché goes, writing my thesis has also been a bumpy road with ups and downs. Therefore, I would like to thank a number of people for their professional and personal support during my thesis process.

First and foremost, I would like to express my gratitude to my supervisors dr. Cees van Beers and dr. Tina Comes for their valuable feedback. Specifically, I would like to thank dr. Cees van Beers for our informative biweekly supervision meetings and his insightful economic perspective on the palladium supply chain. I would like to thank dr. Tina Comes for her valuable feedback on how to quantitatively measure supply chain resilience. Moreover, I would like to thank dr. Benjamin Sprecher and dr. Srijith Balakrishnan for their feedback on the conceptual resilience framework. I would also like to acknowledge Susan van den Brink, for sharing with me previous master's theses that used the Sprecher et al. resilience framework.

Finally, on a more personal note, I would like to express my gratitude to my friends, siblings, parents, and grandparents for their personal support and unwavering confidence in a good outcome.

A.J. van Bree
Delft, February 2024

Executive Summary

Societal & policy relevance

Recent disruptive developments, including the COVID-19 pandemic, war in Ukraine, and shifting geopolitical context of 'great power rivalry', have exposed weaknesses in the global supply chains of critical raw materials (CRMs). Platinum group metals (PGMs) are amongst these raw materials that are considered economically and strategically important by various national governments, but are characterised by significant supply risk. Palladium is a particularly relevant PGM to consider for three reasons. First, palladium has experienced extreme price volatility in recent years, indicating the palladium supply chain's vulnerability to disruptions. Second, palladium's supply is widely regarded as problematic, because of its reliance on a small number of countries, particularly Russia. This dependency on Russian palladium is concerning considering the deteriorating relations between Russia and Western countries. There is a significant risk that Russia will weaponise its dominant position in the palladium supply chain in the coming years by imposing palladium export restrictions. Third, palladium is economically important, because of its critical importance in a wide variety of applications. Palladium is, amongst others, used in the automotive, electronics, and chemical industries.

Considering palladium's critical supply, it is essential to gain insight into the resilience of the palladium supply chain. Accordingly, this study informs policy-makers about potential bottlenecks and historical drivers of resilience in the palladium supply chain.

Research background & research objective

Review of the material criticality and material supply chain resilience literature indicates that, to the best of the author's knowledge, palladium has so far not been studied from a material supply chain resilience perspective. A commonly used conceptualisation of material supply chain resilience is provided by the Sprecher et al. (2015) resilience framework. The framework identifies four resilience mechanisms as the primary drivers of material supply chain resilience:

- The diversity of supply mechanism: the diversity of supply sources. More variety in the sources of supply can reduce the system's vulnerability to disruptions of individual suppliers.
- The price mechanism: the economic feedback loops through which the price affects material supply and demand.
- The stockpiling mechanism: the build-up of stockpiles of a material for future use. Stockpiles can act as a buffer that reduces the impact of temporary supply disruptions.
- The substitution mechanism: the substitution either of the overall technology used in an end-product or of the material used can reduce demand for a material.

This resilience framework has so far not been quantitatively validated. Moreover, existent follow-up studies to the framework have two major limitations. First, these studies have mostly used qualitative methods (i.e. interviews and literature review) rather than quantitative methods to evaluate the resilience mechanisms. Second, they have not systematically explored how a material's resilience overall and the underlying factors that affect this resilience can change over time.

Considering these research gaps, this study investigates the temporal dynamics of the palladium supply chain's resilience using quantitative indicators based on the qualitative Sprecher et al. (2015) framework. Accordingly, this study's main research question can be formulated as follows:

- How has the palladium supply chain's resilience changed over time, and what challenges or opportunities does this imply for policy-makers?

Research approach

In order to address the main research question, this study first conceptualises and operationalises the notions of the palladium supply chain and resilience. The palladium supply chain is defined as the material system that provides palladium required to meet the needs of society. Following Sprecher et al. (2015, the palladium supply chain is then conceptualised as a system consisting of four interlinked resilience mechanisms: the diversity of supply, price, stockpiling, and substitution mechanisms. Resilience is defined as the ability of the palladium supply chain to supply enough palladium to satisfy the demands of society. Accordingly, the palladium supply chain's resilience is operationalised by using the palladium market balance (i.e. supply minus demand).

Subsequently, the four resilience mechanisms are operationalised in terms of a set of quantitative indicator and proxy variables to enable systematic tracking of their evolution over time. Data analysis and regression modelling are then used to investigate how the operationalised resilience mechanisms have changed over time and what these changes imply for resilience.

To investigate the temporal dynamics of the palladium supply chain's resilience overall, a selection of the indicators is used to compute an annual compound resilience index. The resilience index's weighting method is based on Principal Component Analysis.

Finally, the temporal analyses of the resilience mechanisms are translated into recommendations for policy-makers to improve the palladium supply chain's resilience.

Main findings & scientific contributions

The analysis of the diversity of supply mechanism indicated that the country-level concentration of palladium mining has historically been consistently high, but Russian dominance has significantly decreased since the 1960s. Moreover, it was found that the production concentrations of palladium mining on a company and facility level during the last decade have been medium-to-high and low-to-medium, respectively. Furthermore, it was found that global palladium mine production has historically been particularly vulnerable to supply disruptions in Russia and South Africa. Driven by improved collection and recycling efficiency of automotive catalytic converters (autocatalysts), recycling became an increasingly important source of palladium supply this century. This has historically contributed to resilience by diversifying supply away from the countries in which it is geologically concentrated. However, increased recycling has not been able to keep up with palladium's faster growing demand.

The analysis of the price mechanism suggests that the price mechanism has historically contributed to resilience by raising palladium supply, but only slightly and after a delay of at least 6 years. This suggests that the price mechanism can arguably not significantly contribute to resilience during fast disruptions due to the time delay associated with expanding supply. It was found that palladium price increases have historically not led to significantly more palladium recycling within a period of 10 years. By contrast, it was found that price increases, both of palladium itself and of the metals with which palladium is mined together (platinum, nickel), have historically raised palladium mine production, but only slightly and after a delay of at least 6 years. The finding that palladium mine production is relatively unresponsive to price changes can be explained by investors' reluctance to invest in new palladium mine production due to the uncertain palladium price and demand outlook. Interestingly, it was found that palladium mine production has historically been more sensitive to nickel and platinum price changes than to palladium price changes. This can be explained by the finding that, up until 2016, nickel and platinum contributed more to the economic revenue of palladium mines than palladium. However, it was found that palladium's revenue contribution increased significantly in the period 2010-2021 due to the increasing palladium price. Since 2017 palladium has been the largest contributor to the economic revenue of palladium mines, challenging the dominant view in the literature of palladium as a by-product metal.

The analysis of the stockpiling mechanism indicated that palladium stockpiling has historically both positively and negatively affected resilience, depending on the strategy and position of the stockpiling actor. It was found that the lack of transparency regarding palladium stockpiling is problematic from a resilience perspective, because it enables stockpiling actors (particularly Russia) to manipulate the palladium market. Moreover, a trade-off was identified between the short-term positive impact and long-term negative impact of stockpile sales. In the short term, stockpile sales have historically contributed to resilience by providing an additional source of supply during market deficits. In the long term, structural stockpile sales can suppress prices, thereby inhibiting expansion of supply from mining and recycling. Lastly, it was found that total palladium stockpiles significantly declined during the years 2012-2022 due to Russian state and ETF palladium stockpile sales incentivised by the high palladium price. This decline reduced the buffering capacity of the stockpiling mechanism in case of future temporary supply disruptions.

Analysis of the substitution mechanism indicated that substitution has historically not provided much resilience to fast disruptions. It was found that substitution has historically not significantly reduced overall palladium demand in the short term. Possibly, palladium demand is more elastic and the substitution mechanism's effect on resilience is more positive in the longer term. However, the brief reviews of substitutes by palladium application suggest that the inelasticity of palladium demand likely also results from a lack of suitable substitutes. Platinum was identified as the only suitable substitute for palladium's dominant application, i.e. autocatalysts. Substitution of palladium was found to be limited by co-mining of substitutes with palladium; Japanese government subsidies for palladium-based dental alloys; subjective consumer preference; as well as substitutes' lower technical performance and higher price.

In terms of resilience overall, it was found that an increasing resilience index coincided with a decreasing market deficit during the years 2012-2021. This finding indicates an overall improvement of resilience, but still a structural lack of resilience in the last decade.

Finally, quantitative validation of the resilience index suggested that the resilience index is positively correlated with resilience. The resilience index has a relatively strong positive correlation with the palladium market balance and captures the majority of the variability in the market balance for the period 2012-2021. In terms of quantitative validation of the Sprecher et al. (2015) resilience framework, this implies that the diversity of supply, stockpiling, and price resilience mechanisms do indeed significantly correlate with resilience.

Policy recommendations

Based on the findings from the analyses of the resilience mechanisms, three demand-side and four supply-side policy strategies are recommended to further improve the palladium supply chain's resilience. On the demand side, it is recommended to reduce demand for palladium's dominant application: autocatalysts in internal combustion engine vehicles (ICEVs). Therefore, it is recommended to:

- **Promote further acceleration of the electric vehicle (EV) transition.** Analysis of palladium's substitution mechanism suggests that technological substitution of ICEVs by EVs is more promising than material substitution to reduce palladium demand.
- **Promote shared vehicle use and public transport.** Sales of new ICEVs are an important driver of palladium autocatalyst demand. Shared vehicle use and improved public transport could potentially reduce demand for new ICEVs.
- **Loosen vehicle emission regulations for ICEVs.** Stricter vehicle emission regulations require higher palladium contents in autocatalysts and have historically been a major driver of palladium demand.

On the supply side, it is recommended to:

- **Expand strategic stockpiling.** It was found that strategic stockpiles can contribute to resilience by acting as a buffer in case of supply disruptions. However, analysis of the stockpiling mechanism indicated that state palladium stockpiling is currently very limited in the United States and non-existent in the European Union.
- **Promote palladium mining outside Russia.** Analysis of the diversity of supply mechanism suggests that promoting palladium mining outside Russia could significantly reduce primary production concentration on a country, company, and facility level.
- **Improve diplomatic relations with South Africa.** The historical increase in South Africa's market share in global palladium production and South Africa's dominance in global PGM reserves suggest that future primary palladium production is expected to mainly originate from South Africa.
- **Promote recycling of palladium-containing end-of-life (EOL) products, especially electronics.** It was found that recycling has historically contributed to resilience by diversifying supply away from the countries in which it is geologically concentrated. Palladium-containing EOL electronics are currently insufficiently collected, but are expected to become a more important source of recycled palladium. Introducing proper payments for consumers' EOL electronics, stimulating (or requiring) design for recycling and subsidising recycling efficiency R&D can potentially improve electronics recycling.

Contents

Nomenclature

Abbreviations

The following abbreviations (in alphabetical order) are used in this study:

Abbreviation	Definition
ASM	Artisanal and small-scale mining
BEV	Battery electric vehicle
BGS	British Geological Survey
CRM	Critical raw material
DERA	Deutsche Rohstoffagentur (German Mineral Resources Agency)
EOL	End-of-life
EOL-RIR	End-of-life recycling input rate
EPA	Engineering and Policy Analysis
EPRS	European Parliamentary Research Service
ETF	Exchange-traded fund
EU	European Union
EV	Electric vehicle
HHI	Herfindahl-Hirschman Index
ICE	Internal combustion engine
ICEV	Internal combustion engine vehicle
IPA	International Platinum Group Metals Association
JM	Johnson Matthey
JRC	Joint Research Centre
JOGMEC	Japan Oil, Gas and Metals National Corporation
MAVD	Multi-attribute vector distance
NDS	United States National Defense Stockpile
PCA	Principal component analysis
PGE	Platinum group element
PGM	Platinum group metal
REE	Rare earth element
SRB	State Reserve Bureau
UK	United Kingdom of Great Britain and Northern Ireland
USA	United States of America
USGS	United States Geological Survey
WPIC	World Platinum Investment Council

Units of measurement

Precious metals are typically measured in troy ounces (LBMA, 2017). A troy ounce (oz) is equivalent to approximately 31.10 grams. The following units of measurement are used in this study:

Unit of measurement	Definition
koz	thousands of troy ounces
Moz	millions of troy ounces
kg	kilograms

1 Introduction

This chapter begins by introducing critical raw materials and palladium in particular. The subsequent sections discuss this study's motivation, research approach, scientific and policy relevance, and document structure.

1.1. Critical raw materials: a paradigm shift

Critical raw materials (CRMs) are raw materials that are considered to be of great economic importance and are subject to significant supply risk (European Commission, 2023c; Gardner and Colwill, 2018). The ongoing energy and digital transitions continue to push demand for these CRMs (European Commission, 2023c; Reisch, 2022; Rietveld et al., 2022). Indeed, the energy transition is essentially best understood as a materials transition, namely from fossil fuels to metals (Rietveld et al., 2022; Teer and Bertolini, 2022; Wetzels, 2022). Moreover, the increased popularity of digital technologies, such as Internet of Things, cloud computing, and artificial intelligence requires more semiconductors for electronics and data centers, and hence, requires more CRMs as inputs for semiconductor manufacturing (Carrara et al., 2023; Teer and Bertolini, 2022).

While demand for CRMs continues to increase, the global supply chains of these CRMs have been disrupted in recent years by the outbreak of the COVID-19 pandemic and a series of geopolitical crises, including the US-China trade war and war in Ukraine (Buchholz et al., 2022; Sun, 2022).

The COVID-19 pandemic and subsequent policy responses led to shutdowns of mining, refining, and manufacturing facilities and hindered the transportation of goods, putting pressure on CRM production volumes (Buchholz et al., 2022; Deloitte, 2020; MacDonald et al., 2020). Moreover, the pandemic has highlighted the risk of relying on a small number of companies or countries for the supply of critical goods (Rietveld et al., 2022).

The changing geopolitical context of 'great power rivalry' is also posing a growing risk to the supply of CRMs (Teer and Bertolini, 2022). In recent years, economic resources are increasingly being used as levers of power (Blackwill and Harris, 2016; Teer and Bertolini, 2022). The West's geopolitical rivals, most notably Russia and (the People's Republic of) China, could potentially use their dominant positions in several CRM value chains to constrain future exports (Rijksoverheid, 2022; Teer and Bertolini, 2022). For example, in 2010, China halted its exports of rare earth elements (REEs) to Japan in response to a diplomatic incident over the Senkaku/Diaoyu islands (Bradsher, 2010). This 2010 rare earth crisis led to temporary price spikes for REEs and supply shortages for Japan's high-tech industries (Sprecher et al., 2015; 2017). More recently, China threatened to restrict exports of the CRMs gallium and germanium (Reuters, 2023) and Russia restricted its exports of neon gas, which are crucial for semiconductor manufacturing (Reuters, 2022; Teer and Bertolini, 2022). Accordingly, strategic analysts from the Hague Centre for Strategic Studies conclude that 'CRM value chains are [now] in an early stage of being weaponised' (Teer and Bertolini, 2022, p. 5).

These recent developments have thus exposed the weaknesses of what some scholars refer to as the 'neoliberal' paradigm (e.g., Wetzels, 2022). That is, the dominant paradigm in the late 20th and early 21st-century which advocated globalised, specialised, and efficient supply chains (EPRS, 2022b; Wetzels, 2022). Given recent developments, some industry executives and scholars even go as far as to say that 'globali[s]ation is dead' (O'Sullivan, 2019; Wu, 2023). Consequently, supply chain management is experiencing a paradigm shift away from cost-efficient just-in-time delivery towards making supply chains more resilient to disruptions (EPRS, 2022b; Rietveld et al., 2022). Policy-makers and firm-level decision-makers have recently become more aware of the risks threatening the supply of CRMs and are increasingly applying strategies to promote supply chain resilience (IEA, 2020; Rietveld et al., 2022).

This global paradigm shift is also noticeable in policy-making within the European Union (EU). In the words of EU commissioner Thierry Breton: 'we are seeing the end of an economic era dominated by a long-standing belief in just-on-time logistics, geographical specialisation and elongated supply chains' (Breton, 2022, p. 2). As an alternative to the neoliberal paradigm, the EU now strives, not for complete self-sufficiency, but for so-called 'open strategic autonomy' (Breton, 2022; Rietveld et al., 2022). That is, a policy strategy that aims to improve the EU's capability to act autonomously in strategically important policy areas without being too dependent on other countries, particularly in terms of the supply of CRMs (EPRS, 2022a; Rietveld et al., 2022).

Currently, however, the EU is still highly dependent on non-EU countries for the supply of CRMs (Teer and Bertolini, 2022). For example, the EU has an average import reliance of 77% and 54% for extraction and processing of CRMs for wind energy, respectively (Van Halm, 2023). Even prior to recent crises, the EU launched several policy initiatives to reduce its dependence on third countries (Rietveld et al., 2022).

In 2008, the EU launched the EU Raw Materials Initiative (RMI). This policy initiative aims to reduce the EU's dependencies on third countries in order to 'secur[e] non-energy raw materials for EU industrial value chains and societal well-being' (European Commission, 2023c, p. 1). To reduce dependencies, the initiative promotes diversification of primary supply (i.e. mining) outside the EU, domestic sourcing, resource efficiency, and development of secondary supply (i.e. recycling) (Rietveld et al., 2022). As part of the RMI, the European Commission has published material criticality assessment studies every three years since 2011, which identify a list of CRMs for the EU (European Commission, 2023c).

In March 2023, the European Commission also proposed a European Critical Raw Materials Act (CRMA). The CRMA sets out more concrete targets to reduce dependencies. First, at least 10% of the EU's annual consumption for extraction should come from domestic mining. Second, at least 40% of the EU's annual consumption for processing should come from domestic processing. Third, at least 15% of the EU's annual consumption for recycling should come from domestic recycling. Finally, no more than 65% of the EU's annual consumption for any strategic raw material should come from a single third country (European Commission, 2023a).

1.2. Introduction to palladium

Amongst the materials that have been designated as CRMs for the EU are the platinum group metals (PGMs), also referred to as platinum group elements (PGEs) (European Commission, 2023c). The EU has designated the PGMs as critical for the EU in all five EU CRM assessments published since 2011 (European Commission, 2023c). The PGMs are also considered economically and strategically important by various national governments, including Japan, the United States (US), Canada, and Australia (Institute of Materials, Minerals and Mining, 2022; Su and Hu, 2022; USGS, 2022).

Palladium (Pd) is one of the six PGMs, together with platinum, iridium, rhodium, ruthenium, and osmium (European Commission, 2023c). Palladium was first isolated by the English chemist William Wollaston in 1803 and named after the asteroid Pallas (Encyclopaedia Britannica, 2023). The precious gray-white metal with atomic number 46 has several desirable chemical properties, including a relatively high melting point (1555∘C), a relatively high density (12.02 g/cm^3), relatively strong resistance to corrosion, and superior catalytic activity (Encyclopaedia Britannica, 2023; Gunn and Benham, 2009). Palladium is a particularly relevant material to consider for three main reasons.

First, palladium has experienced extreme price volatility in recent years (DeCarlo and Goodman, 2022; Georgitzikis et al., 2023), also relative to the other volatile PGMs (see Figure 1.1). Such material price volatility is an indicator of a material supply chain's vulnerability to disruptions (Van de Camp, 2020). Indeed, metal price spikes often indicate that the metal supply provided by the supply chain cannot keep up with demand (Kleijn et al., 2011).

Second, palladium's supply is widely regarded as problematic, because of its reliance on a small number of countries, particularly Russia (Georgitzikis et al., 2023; Teer and Bertolini, 2022). Indeed,

Figure 1.1: Nominal daily palladium and platinum prices in USD/troy ounce during the period January 2006-February 2023. Note that the palladium price has been higher and more volatile than the platinum price since 2018. Figure adopted from Georgitzikis et al. (2023).

the most significant supplier of palladium is Russia, accounting for around 40% of global palladium production (Carrara et al., 2023). This dependency on Russian palladium is concerning considering the deteriorating relations between Russia and Western countries. In early 2022, even prior to the Russian invasion of Ukraine, the White House issued a warning to the American semiconductor industry to reduce its dependence on Russian palladium through supply chain diversification (Alper and Freifeld, 2022; DeCarlo and Goodman, 2022). Similarly, in early 2023, Citigroup warned its clients about the risk of Russia weaponising its palladium exports (Hook and Dempsey, 2023). As relations between the West and Russia continued to deteriorate after the Russian invasion of Ukraine, strategic analysts from The Hague Centre for Strategic Studies cautioned that '[t]he continuation of palladium exports from Russia [$\cdots$] should not be taken for granted' (p. 22). Accordingly, a survey of geopolitical experts conducted by the strategic analysts indicated that palladium export restrictions imposed by Russia are deemed 'more likely than not' in the next few years (Teer and Bertolini, 2022, p. 13).

Third, palladium is economically important, because of its critical importance in a wide variety of applications. Due to its desirable chemical properties, palladium is used for applications in a wide variety of sectors: automotive (88%), electronics (4%), chemicals (3%), dental (2%), jewellery (2%), and others (1%) (European Commission, 2023c). Palladium's most common application is in automotive catalytic converters (also known as autocatalysts) in internal combustion engine vehicles (ICEVs), where it aids to decrease air pollutant emissions (DeCarlo and Goodman, 2022; Nassar, 2015). In the electronics sector, palladium is used as an adhesion layer in semiconductors (DeCarlo and Goodman, 2022; Nassar, 2015). This makes palladium a critical input for manufacturing semiconductors (DeCarlo and Goodman, 2022), which have been described as the 'oil of the 21^{st} century' considering their ubiquitous use in all sorts of applications (Teer and Bertolini, 2022, p. 1). In the chemical industry, palladium is used as a catalyst in chemical processes (Miller et al., 2017). Palladium is also used as an alloy in dental and jewellery applications due to its high resistance to corrosion (Encyclopaedia Britannica, 2023).

1.2.1. Palladium processing

Palladium can be obtained either by mining palladium-containing ores or by recycling end-of-life (EOL) products that contain palladium. In the remainder of this study, palladium obtained from ore mining and recycling are referred to as primary and secondary supply, respectively.

Primary palladium supply is derived from deposits of palladium-containing ores. In these deposits, palladium is not found in isolation, but in metallic alloys with other PGMs, gold, silver, nickel, and copper (Encyclopaedia Britannica, 2023; Gunn and Benham, 2009). Accordingly, all primary commercial sources of palladium supply are linked to mining operations of other metals (DeCarlo and Goodman, 2022; Encyclopaedia Britannica, 2023). Although palladium occurs in many different forms depending on the specific deposit, a general distinction can be made between two types of palladium-containing ores: copper-nickel-dominant ores and PGM-dominant ores (Gunn and Benham, 2009). The former are primarily found in the Ural Mountains in Russia, whereas the latter are primarily found in the Transvaal region of South Africa (Encyclopaedia Britannica, 2023; Gunn and Benham, 2009). Extraction of palladium from these ores involves a complex series of pyro- and hydrometallurgical processing steps, which varies depending on the specific type of ore. Typically, extraction of palladium from ores involves crushing and grinding the mined ore, creating a concentrate, smelting, and finally refining the concentrate to higher purities (Crundwell et al., 2011; Gunn and Benham, 2009). Extraction of palladium from mined ores is a complex and energy intensive process due to the low concentration of palladium in ores at only 2-7 grams per tonne of ore (Crundwell et al., 2011; Nose and Okabe, 2014).

Alternatively, secondary palladium supply can be derived from recycling palladium-containing EOL products, particularly spent autocatalysts. Similar to extraction from ore, this involves a series of complex processing steps, including crushing, smelting, and refining (Nose and Okabe, 2014).

1.3. Thesis approach and relevance

This section first introduces the research gaps identified in the literature. Subsequently, this study's methodological approach, its scientific and policy relevance, and its relevance to the Engineering and Policy Analysis (EPA) master's programme are discussed. Finally, the document structure is outlined.

1.3.1. Research gaps

Considering palladium's economic importance and its exposure to disruption risks, it is essential to gain insight into the palladium supply chain's resilience. That is, the palladium supply chain's ability to supply enough palladium to satisfy the demands of society, especially during supply disruptions. A review of related material criticality and material supply chain resilience literature indicates that palladium has previously been studied from a material criticality perspective (Schrijvers et al., 2020), but not from a material supply chain resilience perspective. These criticality assessments, however, have several limitations. First, these assessments typically evaluate the criticality of multiple materials and do not focus solely on palladium. Second, these studies often do not differentiate between palladium and other PGMs, despite the fact that these metals can have very different supply situations and applications (Schrijvers et al., 2020). Third, these criticality assessments do not offer much guidance in terms of formulating risk-mitigating strategies due to the aggregated nature of their results (Bustamante et al., 2018). Finally, most criticality assessments provide a static rather than a dynamic perspective on criticality (Dewulf et al., 2016; Mancheri et al., 2018; Van den Brink et al., 2022).

Studying materials from a resilience perspective provides a promising alternative approach that is more forward-looking and better accounts for the dynamic nature of material criticality (Dewulf et al., 2016; Schrijvers et al., 2020; Van den Brink et al., 2022). Sprecher et al. (2015) introduced a qualitative resilience framework that can be used to study the resilience of material supply chains. This framework has so far not been quantitatively validated. Based on a case study of the neodymium supply chain, the authors postulate that four mechanisms are primarily responsible for the resilience of material supply chains (Sprecher et al., 2015):

- The diversity of supply mechanism: the diversity of supply sources. More variety in the sources of supply can reduce the system's vulnerability to disruptions of individual suppliers.
- The price mechanism: the economic feedback loops through which the price affects material supply and demand.
- The stockpiling mechanism: the build-up of stockpiles of a material for future use. Stockpiles can act as a buffer that reduces the impact of temporary supply disruptions.
- The substitution mechanism: the substitution either of the overall technology used in an end-product or of the material used can reduce demand for a material.

Building on this framework, a small number of studies has studied material supply chain resilience for various materials (e.g., Galimberti, 2021; Mancheri et al., 2018; Van de Camp, 2020; Van den Brink et al., 2022). However, the Sprecher et al. (2015) resilience framework has so far not been used to study palladium. Furthermore, these studies have not systematically explored how a material's resilience overall and the underlying factors that affect this resilience can change over a period of multiple years. Accordingly, more research is required to investigate how the resilience of material supply chains can change over time (Van den Brink et al., 2020).

1.3.2. Research approach & questions

Considering the research gaps outlined above, this thesis studies how the palladium supply chain's resilience has changed over time. Moreover, it is investigated what challenges and opportunities this implies for policy-makers. Accordingly, this thesis's main research question can be formulated as follows:

- How has the palladium supply chain's resilience changed over time, and what challenges or opportunities does this imply for policy-makers?

In order to address this main research question, the qualitative resilience framework by Sprecher et al. (2015) is used as a starting point. The palladium supply chain is conceptualised as a system consisting of the four interlinked resilience mechanisms identified by Sprecher et al. (2015). Resilience is operationalised by using the palladium supply-demand balance. Subsequently, this study follows a quantitative observational research approach. First, the four resilience mechanisms are operationalised in terms of a set of indicator and proxy variables to enable systematic tracking of their evolution over time. Data corresponding to these proxies is collected and pre-processed to enable further analysis. Second, data analysis is used to investigate how the operationalised resilience mechanisms have changed over time and what these changes imply for resilience. In particular, the correlation between the resilience mechanisms' proxies and the palladium supply-demand balance is investigated to evaluate the validity of the Sprecher et al. (2015) framework. Finally, the implications of the change in the resilience mechanisms are investigated in terms of challenges and opportunities for policy-makers. Hence, in order to answer the main research question, the following sub-questions are considered in this study:

1. How can the four resilience mechanisms be operationalised, considering data availability and quality?
2. How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?
3. Given how the four resilience mechanisms have changed over time, what recommendations can be made to policy-makers to promote the palladium supply chain's resilience?

1.3.3. Scientific & policy relevance

In terms of scientific relevance, this thesis contributes to the existing material supply chain resilience literature in four main ways.

First of all, this study provides a quantitative evaluation of the validity of the Sprecher et al. (2015) resilience framework. To date, the material supply chain resilience framework has only been qualitatively validated through case studies of historical disruptions (e.g., Sprecher, 2017).

Second, this is the first study in which palladium is analysed from a material supply chain resilience perspective. Compared to a criticality approach, a resilience approach adds a dynamic perspective by evaluating how resilience-promoting mechanisms can change over time (Mancheri et al., 2018; Van den Brink et al., 2022). Studying the palladium supply chain using a resilience approach can also contribute to a better understanding of palladium's material criticality. After all, criticality and resilience are essentially two sides of the same coin, since a material's criticality can be defined in terms of how resilient the material's supply chain is (Dewulf et al., 2016; Sprecher et al., 2015). Moreover, analysing the palladium supply chain from a resilience perspective also allows for comparison of the resilience of different material supply chains.

Third, compared to the existent follow-up studies to the Sprecher et al. (2015) resilience framework, this study uses a more quantitative approach to evaluate the resilience mechanisms. Instead of heavily relying on stakeholder interviews (e.g., Sprecher et al., 2015; Sprecher et al., 2017; Van de Camp, 2020), this study operationalises the resilience mechanisms in terms of quantitative indicators. Moreover, this study takes a more dynamic perspective by systematically exploring how the resilience of a material supply chain and the underlying factors that affect this resilience can change over time.

Finally, this thesis provides an up-to-date and in-depth overview of the palladium supply chain. This is relevant considering the dynamic nature of material criticality and resilience, which change continually over time (Graedel et al., 2015; Van den Brink et al., 2020). Moreover, information about the palladium supply chain is spread across a wide range of news articles, industry reports, and company (annual) reports, public databases, and academic publications. This is further complicated by the fact that these sources often do not differentiate between the different PGMs (Schrijvers et al., 2020). This study, in contrast, combines data from a variety of public sources to provide an up-to-date overview of the supply chain of palladium specifically.

In terms of policy relevance, this study can contribute to the formulation of policy regarding the palladium supply chain and CRMs more generally by focusing on resilience. Indeed, such a resilience approach to policy-making is appropriate when dealing with material supply chains characterised by deep uncertainty (Kwakkel and Pruyt, 2015; Pruyt, 2010; Walker et al., 2013). More specifically, this study can inform policy-makers about the current level of resilience and potential bottlenecks for the palladium supply chain. Such '[a]wareness of resilience enables one [⋯] to preserve or enhance a system's own restorative powers' (Meadows, 2008, p. 78). Moreover, this study provides policy recommendations on how to improve the palladium supply chain's resilience to better cope with future disruptions.

1.3.4. Relevance to the EPA programme

This master's thesis is conducted in partial fulfillment of the requirements for the degree Master of Science in Engineering and Policy Analysis at the TU Delft. The EPA master's programme focuses on analysing international grand challenges that arise from complex multi-actor systems. Fundamental themes in the master's programme are systems thinking, modelling, and public policy.

This thesis relates to the themes of the EPA programme in several ways.

Firstly, this thesis relates to the grand societal challenge of metals scarcity (Kwakkel and Pruyt, 2015). Palladium's status as a critical raw material and its market imbalances result from this scarcity. In fact, this thesis investigates the palladium supply chain's resilience, defined as the supply chain's ability to satisfy demand, precisely because of the mismatch between demand and scarce metal supply.

Secondly, this thesis applies systems thinking and conceptual system's modelling. The temporal dynamics of the palladium supply chain system's resilience are investigated. Such material supply chains, including the palladium supply chain, are complex adaptive systems and resilience can be considered as an emergent property of this system (Choi et al., 2001; Sprecher et al., 2017; Van de Camp, 2020). Moreover, following Sprecher et al. (2015), this study explicitly conceptualises the palladium supply chain as a system consisting of four resilience mechanisms that are interlinked by feedback loops.

Thirdly, this thesis applies conceptual modelling and statistical modelling to investigate the palladium supply chain. Conceptual models of the palladium supply chain overall and the price mechanism are presented in Chapters 3 and 4, respectively. Chapters 6 and 8 use regression modelling of the (cross) price elasticities to investigate the price and substitution mechanisms, respectively.

Lastly, this thesis investigates the palladium supply chain from a multi-actor and public policy perspective. This thesis's analysis of the resilience mechanisms explicitly accounts for the multi-actor context of the palladium supply chain. For example, the analysis of the diversity of supply mechanism distinguishes between diversity of supply on a country, company, and facility level. Thereby, this thesis recognises states, mining companies, and individual mine operators as distinct actors that can affect palladium supply on different levels. Similarly, the analysis of the stockpiling mechanism makes a distinction between stockpiling by states, companies, and investors. The analysis of the stockpiling mechanism illustrates that these actors can have different objectives and, consequently, different impacts on resilience. Furthermore, this thesis's main research question is explicitly aimed at informing policy-makers about the bottlenecks and resilience of the palladium supply chain and provides recommendations to policy-makers in Chapter 9.

1.3.5. Thesis structure

This study is organised as follows: Chapter 2 discusses the existent literature related to material criticality and material supply chain resilience. Subsequently, Chapter 3 outlines the methods and data sources used in this study. Chapter 4 discusses how the four resilience mechanisms are operationalised. Chapters 5, 6, 7, and 8 then describe the results of the analyses of the diversity of supply, price, stockpiling, and substitution mechanisms, respectively. Chapter 9 discusses the implications of the analyses of the four resilience mechanisms for policy-makers and proposes policy recommendations. Subsequently, Chapter 10 discusses the relevance and limitations of this study's findings. Finally, Chapter 11 summarises this study's findings and addresses the main research question.

2
Literature overview

This chapter discusses the existent literature related to material criticality and resilience of material supply chains.

2.1. Material criticality assessments

In line with the growing awareness of risks to the supply of CRMs, there has been growing interest in the scientific study of raw material criticality in the last 15 years (Dewulf et al., 2016). The US National Research Council (National Research Council, 2008) was the first to systematically evaluate raw material criticality (Schrijvers et al., 2020). Following this approach, most subsequent material criticality assessments conceptualise criticality as comprising of at least two dimensions: supply risk and vulnerability (Dewulf et al., 2016; Schrijvers et al., 2020; Sun, 2022). There is a lack of consensus concerning the definition and measurement of raw material supply risk and vulnerability (Achzet and Helbig, 2013; Dewulf et al., 2016; Helbig et al., 2016). Raw material supply risk is often understood as the probability of a supply disruption (Achzet and Helbig, 2013; Dewulf et al., 2016; Schrijvers et al., 2020). Raw material vulnerability is often understood as the potential economic impact of a supply disruption (Dewulf et al., 2016; Helbig et al., 2016; Schrijvers et al., 2020). There is no generic standard approach to measure material criticality and criticality assessment studies have used a heterogeneous range of indicators to quantify supply risk and vulnerability (Achzet and Helbig, 2013; Dewulf et al., 2016; Schrijvers et al., 2020).

These material criticality assessments typically evaluate the criticality of multiple materials. Palladium has also previously been studied from such a material criticality perspective (Schrijvers et al., 2020). These criticality assessments, however, have several limitations.

Firstly, criticality assessments often do not differentiate between the individual PGMs, despite the fact that these metals can have very different supply situations and applications (Schrijvers et al., 2020).

Secondly, in several criticality assessments, the geographical scope of the system under consideration is regional or national rather than global (Dewulf et al., 2016; Schrijvers et al., 2020), despite the fact that material supply chains are highly globalised. For example, the criticality assessments by the European Commission (European Commission, 2020, 2023c) evaluate the criticality of materials from the perspective of the EU. Taking such a regional or national perspective is problematic, however, because the supply chains of materials are fundamentally global. Accordingly, I argue that designing effective risk-mitigating policies requires taking a global rather than a regional or national perspective.

Thirdly, criticality assessments do not offer much guidance in terms of formulating risk-mitigating strategies due to the aggregated nature of their results (Bustamante et al., 2018). For example, the criticality assessments by the European Commission provide two main metrics to measure criticality: a supply risk score and an economic importance score (European Commission, 2020, 2023c). Such aggregated scores are effective tools to compare the relative criticality of multiple materials, e.g. palladium compared to cobalt (Bustamante et al., 2018). However, to formulate risk-mitigating strategies for a specific material, it would be useful to evaluate the individual underlying mechanisms that affect a material's criticality in more detail.

Finally, material criticality assessments provide insight into disruptions that a material supply chain may undergo and their potential impact, however they do not provide systematic insight into how that material supply chain could respond and potentially mitigate or absorb disruptions (Dewulf et al., 2016; Schrijvers et al., 2020). The latter, however, is crucial to inform the formulation of risk-mitigating policies. Most criticality assessments are thus backward-looking rather than forward-looking by providing a static rather than a dynamic perspective on criticality (Dewulf et al., 2016; Mancheri et al., 2018; Van den Brink et al., 2022). An exception is the criticality assessment by Rosenau-Tornow et al. (2009), which takes a more forward-looking approach by considering future market capacity, degree of exploration, and investment in mining as criticality indicators.

The European Commission aims to account for this final limitation of taking a retrospective approach to criticality by publishing separate foresight studies alongside the criticality assessments (e.g., Carrara et al., 2023). However, a promising alternative approach that is inherently more dynamic is to study materials from a resilience perspective (Dewulf et al., 2016; Mancheri et al., 2018).

2.1.1. From criticality to resilience

Dewulf et al. (2016) distinguish between criticality assessments that measure the criticality of a material and resilience studies that address the way the material supply chain is able to respond to this criticality. Accordingly, the authors argue that studying a material from a resilience perspective could be interpreted as an extension of criticality screening (Dewulf et al., 2016). In line with this reasoning, Sprecher et al. (2015) argue that a material's criticality can be defined in terms of how resilient the material's supply chain is.

The distinction between criticality and resilience for raw materials relates to the notions of supply risk, vulnerability, and resilience for supply chains more generally. Whereas criticality assessments provide insight into the supply risk and vulnerability of a material's supply chain, they generally do not provide much insight into the ability of the material supply chain to overcome this vulnerability, i.e. resilience (cf. Heckmann et al., 2015).

2.2. Resilience for material supply chains

For systems in general, the notion of resilience refers to a system's ability to retain its structure and function when exposed to disruptions (Fiksel, 2006; Meadows, 2008; Sprecher et al., 2015). Put simply, resilience is a system's capacity to deal with disruptions (Dewulf et al., 2016; Sprecher et al., 2015). Material supply chain systems are subject to disruptions that are inherently difficult or even impossible to predict, which have previously been referred to as Black Swans (Sprecher et al., 2017; Taleb, 2007). Material supply chains are complex adaptive systems (Choi et al., 2001; Van de Camp, 2020; Sprecher et al., 2017) characterised by deep uncertainty (Kwakkel and Pruyt, 2015; Pruyt, 2010). More specifically, the presence of Black Swans indicates the deepest level of recognised uncertainty, i.e. Level 5 uncertainty (Walker et al., 2013). Resilience offers an appropriate policy-making approach to cope with such Level 5 uncertainty (Walker et al., 2013). Moreover, resilience theory offers an effective theoretical framework to study how material supply chains respond to disruptions (Castillo-Villagra and Thoben, 2022; Mancheri et al., 2019).

Application of resilience theory in the context of material supply chains is a relatively recent approach that requires further exploration (Dewulf et al., 2016; Schrijvers et al., 2020; Sprecher et al., 2015). Accordingly, there is currently no consensus about the definition of material supply chain resilience (Castillo-Villagra and Thoben, 2022). However, a commonly used conceptualisation of material supply chain resilience is provided by Sprecher et al. (2015) (Castillo-Villagra and Thoben, 2022). In 2015, Sprecher et al. introduced a novel resilience framework for material supply chains specifically. The authors use the neodymium magnet (NdFeB) supply chain as a case study. The following sections discuss the qualitative Sprecher et al. (2015) resilience framework and related studies in more detail.

2.2.1. The Sprecher et al. (2015) resilience framework

The Sprecher et al. (2015) resilience framework distinguishes between four general types of disruptions for material supply chains, based on the disruption's relative position on a supply-demand axis and slow-fast axis:

- Supply-fast: these are short-term developments (events) that disrupt the supply of a material. Examples include political issues (such as export restrictions) and disruptions of production facilities due to natural disasters, epidemics, or strikes.

- Supply-slow: these are long-term developments that disrupt the supply of a material. Examples include technological innovations that would improve the efficiency of mining, refining, or recycling processes.
- Demand-fast: these are short-term developments (events) that disrupt the demand of a material. Examples include the introduction of regulations that either lead to less (e.g., prohibition of asbestos use) or more material demand (e.g., stricter regulation for car emissions).
- Demand-slow: these are long-term developments that disrupt the demand of a material. Examples include technological breakthroughs in substitution or product design that lead to a replacement of or a reduction in the material used.

Resilience to such system disruptions is provided by several feedback mechanisms in a system's structure that restore the system in case of disruptions (Meadows, 2008). For material supply chain systems, Sprecher et al. define resilience as 'the capacity to supply enough of a given material to satisfy the demands of society, and to provide suitable alternatives if insufficient supply is available' (2015, p. 6741). Taking an industrial ecology approach to resilience, the authors then conceptualise the resilience of a material supply chain system as depending on three factors (Sprecher et al., 2015):

- Resistance: the system's ability to directly maintain function during a disruption.
- Rapidity: the system's ability to rapidly recover within a short period after the disruption.
- Flexibility: the system's ability to switch between alternative subsystems to meet supply needs during a disruption.

This conceptualisation of resilience shows that resilience should not be conflated with robustness (Van de Camp, 2020). For comparison, Miroudot defines supply chain robustness as 'the ability to maintain operations during a crisis' (2020, p. 122). Hence, robustness is similar to resistance, i.e. one particular aspect of resilience (Van de Camp, 2020).

Based on these three resilience-contributing factors, Sprecher et al. (2015) postulate that four mechanisms (i.e. sub-systems) are the primary drivers of a material supply chain's resilience:

- The diversity of supply mechanism: the diversity of supply sources. More variety in the sources of supply can reduce the system's vulnerability to disruptions of individual suppliers. This mechanism can thus improve resistance and rapidity.
- The stockpiling mechanism: the build-up of stockpiles of a material for future use. Stockpiles can act as a buffer that reduces the impact of temporary supply disruptions. This mechanism thus improves resistance.
- The substitution mechanism: the substitution either of the overall technology used in an end-product or of the material used can reduce demand for a material. This mechanism can thus improve flexibility.
- The improving material properties mechanism: the improvement of the properties of a material to maintain product functionality, while using less of the material. This mechanism can thus improve resistance.

These four mechanisms are interlinked through various feedback loops. The most important of these feedback loops are the economic feedback loops through which the price affects material supply and demand (Sprecher et al., 2015). Together these economic feedback loops are referred to as the price mechanism (Sprecher et al., 2015, 2017).

To date, the Sprecher et al. (2015) resilience framework has not been quantitatively validated. Arguably this can be explained by the fuzzy definitions of material supply chain resilience and the resilience mechanisms provided by the authors. These fuzzy definitions complicate the operationalisation of resilience and the resilience mechanisms into measurable indicators required for quantitative validation.

Instead, several recent studies have built upon the resilience framework using mostly qualitative approaches to analyse material supply chains. The framework has been used to analyse the supply chains of neodymium (Sprecher et al., 2015, 2015, 2017), tantalum (Mancheri et al., 2018), cobalt (Van de Camp, 2020), tin (Galimberti, 2021), and antimony (Van den Brink et al., 2022). However, to the best of the author's knowledge, the resilience framework has so far not been applied to palladium.

2.3. Follow-up studies to the Sprecher et al. (2015) resilience framework

Six studies are identified that analyse material supply chains based on the resilience mechanisms in the Sprecher et al. (2015) framework (see Table 2.1). The small number of studies, which include two master's theses, indicate that this is a relatively recent and under-explored approach to material supply chain resilience. This section discusses similarities, differences, and limitations of these resilience studies.

Study	**Material**	**Metal mostly mined as companion?**
Sprecher et al. (2015, 2017)	Neodymium (Nd)	Yes
Mancheri et al. (2018)	Tantalum (Ta)	No
Van de Camp (2020)	Cobalt (Co)	Yes
Galimberti (2021)	Tin (Sn)	No
Van den Brink et al. (2022)	Antimony (Sb)	Yes

Table 2.1: Overview of studies that use the Sprecher et al. (2015) resilience framework. A metal is mostly mined as a companion if the share of global production obtained as companion exceeded 50% in 2008, based on Nassar et al. (2015, see supplement).

A first notable difference between the resilience studies concerns the type of metal considered. For a given mine, a metal can either be mined as the main product, referred to as the host, or not, in which case it is referred to as a companion (Nassar et al., 2015). Mancheri et al. (2018) and Galimberti (2021) investigated tantalum and tin, respectively, which are mostly mined as hosts. The remaining studies investigated neodymium, cobalt, and antimony, which are mostly mined as companions. As will become clear in the remainer of this study, material's status as a companion metal is a relevant factor to consider when studying material supply chain resilience (Van den Brink et al., 2022).

Another difference between the resilience studies concerns the resilience mechanisms that are investigated. Sprecher et al. (2015, 2017) discuss diversity of supply, stockpiling, substitution, and improving material properties as the four main resilience mechanisms and discuss the price mechanism as a separate set of overarching feedback loops. This conceptual distinction between the four resilience mechanisms on the one hand and the feedback loops through the price mechanism on the other hand is arguably somewhat superficial, since the identified resilience mechanisms are essentially also sub-systems consisting of feedback loops. Accordingly, Van den Brink et al. (2022) identify the price mechanism as a resilience-promoting mechanism in its own right. Moreover, it can be noted that Sprecher et al. (2015, 2017) identify substitution and improving material properties as two distinct resilience mechanisms [1], whereas the other studies do not explicitly address improving material properties. Overall, the common denominator between the identified resilience studies is that they essentially all recognise the importance of the price mechanism, diversity of supply (both primary and secondary supply), stockpiling, and substitution in the context of resilience. Hence, these four resilience mechanisms are considered in the remainder of this study.

A limitation of the studies overall is that they do not systematically explore how resilience for their respective material supply chains has changed over time. For example Van de Camp (2020) and Galimberti (2021) explicitly focus on the current level of resilience in their research questions. Sprecher et al. (2015, 2017) primarily focus on resilience during the 2010 REE crisis. Van den Brink et al. (2022) primarily focus on resilience for the selected base year 2018. However, material criticality is fundamentally time-dependent: it changes over time due to discovery of new deposits, changing political circumstances, technological innovations (Graedel et al., 2015), and business consolidation. Accordingly, resilience (to criticality) is also fundamentally time-dependent (Van den Brink et al., 2022). Hence, more research is required to investigate how resilience of material supply chains can change over time (Van den Brink et al., 2020).

Another major limitation of the studies is that have mostly used qualitative methods to evaluate the

[1] The rationale behind the distinction between substitution and improving material properties is that the two mechanisms relate to different supply chain actors and different aspects of resilience: substitution relates to the product design stage and flexibility, whereas improving material properties relates to the production stage and resistance (Sprecher et al., 2015; Van de Camp, 2020).

resilience mechanisms. Consequently, the evaluation of resilience is rather subjective. The qualitative indications of resilience used (i.e. low, medium, high) are typically not based on objective thresholds. For example, Van den Brink et al. (2022) indicate the resilience of the antimony supply chain's substitution mechanism as 'medium', but do not provide objective criteria to substantiate why the level of resilience is considered medium and not low or high.

The material supply chain resilience studies also differ in the methodologies they use to evaluate the resilience mechanisms, which is discussed in the next subsection.

2.3.1. Evaluation of resilience mechanisms

The resilience framework introduced in the original paper by Sprecher et al. (2015) is qualitative in nature and the authors use a combination of literature review and interviews to evaluate the four resilience mechanisms. In a follow-up study, the authors aim to evaluate each of the resilience mechanisms in a more quantitative way by introducing three quantitative resilience mechanism parameters (Sprecher et al., 2017):

- Time lag (years): the time between the start of the disruption and the moment a countermeasure starts to have a quantifiable effect on the system. For example, the time between a supply disruption and a new mine to come online.
- Response speed (% of overall market volume per year): the speed with which a mechanism can scale. For example, the speed with which a producer can scale up production.
- Maximum magnitude (% of overall market volume): the maximum magnitude of the effect of a mechanism. For example, the maximum amount of recycling that is practically possible.

The authors call for an application of these quantitative resilience metrics to other material supply chains (Sprecher et al., 2017). Amongst the identified studies, the only study that attempted this approach is Van de Camp (2020). However, rather than quantifying the response speed in terms of physical units (i.e. % of overall market volume per year), this study used a qualitative classification to denote the type of learning curve (i.e. linear, exponential, logarithmic, or logistic). This illustrates that the quantitative resilience metrics proposed by Sprecher et al. (2017) are not very practical. In general, it is difficult to obtain quantitative data when investigating critical materials (Schrijvers et al., 2020; Sprecher et al., 2017; Wagner et al., 2019). To obtain the type of data required for the three quantitative resilience metrics, Sprecher et al. (2017) and Van de Camp (2020) heavily relied on interviews with stakeholders. It can be difficult to obtain the required data through interviews, for example, because companies might be reluctant to disclose sensitive information. As a case in point, Galimberti (2021) 'intended [his literature review] to be complemented by interviews made to actors of the supply chain', but did not receive sufficient responses (2021, p. 19). Even if interviews are conducted, the final selection of participants willing to be interviewed may be selective. Moreover, the data obtained through interviews is arguably subjective and might only reflect the position of a specific stakeholder.

Unsurprisingly then, the follow-up studies to the Sprecher et al. (2015) framework have used different qualitative and quantitative methods rather than interviews to evaluate the four resilience mechanisms. The following subsections discuss the methods used in these follow-up resilience studies to evaluate the four resilience mechanisms as well as other literature related to these four mechanisms.

2.4. The diversity of supply mechanism

A distinction can be made between three sources of supply: primary supply (i.e. supply from ore mining), secondary supply (i.e. supply from recycling), and artisanal & small-scale mining (ASM)[2] (Sprecher et al., 2015). Previous studies found that data related to ASM is often difficult to obtain, because supply from ASM is often not included in official trade statistics (e.g., see Mancheri et al., 2018; Sprecher et al., 2017 ; Van den Brink et al., 2022).

Regarding primary supply, the concentration of reserves can provide insight into where (future) primary production can occur and indicates whether geographic diversification is possible (Rietveld et al., 2022). Reserves are the occurrences (deposits) of a material that are economically feasible to mine (Rietveld et al., 2022). Material criticality assessments, however, generally do not use reserves data

[2] The OECD defines ASM as 'formal or informal mining operations with predominantly simplified forms of exploration, extraction, processing, and transportation.' ASM is typically low capital-intensive and high labour-intensive (2013, p. 65).

(Rietveld et al., 2022). Amongst the identified material supply chain resilience studies, only Mancheri et al. (2018) investigated the concentration of reserves to evaluate the diversity of supply mechanism.

Instead, material criticality assessments have typically evaluated diversity of supply by measuring production concentration on a country, and sometimes company, level (Schrijvers et al., 2020; Van den Brink et al., 2020). To measure production concentration, these studies have typically used the Herfindahl-Hirschman Index (HHI) (Schrijvers et al., 2020; Silberglitt et al., 2013). The HHI is calculated by computing the sum of the squared market shares of producers (e.g., countries or companies). This results in a HHI score between 0 and 10,000, where a value of 10,000 (i.e., 100^2) corresponds to a single-producer monopoly (Sprecher et al., 2017). HHI values above 1500 and 2500 indicate moderately and highly concentrated markets, respectively (Silberglitt et al., 2013; Van den Brink et al., 2022). Similar to most criticality assessments, most of the identified material supply chain resilience studies measured the concentration of production on a country level by computing the country-level HHI (e.g., Galimberti, 2021; Sprecher et al., 2017; Van de Camp, 2020; Van den Brink et al., 2022). With the exception of Van den Brink et al. (2022), material criticality assessments and previous material supply chain resilience studies have thus under-explored the facility-level production concentration. This can be explained by the poor availability of CRM mining data on a sub-national level of granularity (Jasansky et al., 2023).

However, evaluating the diversity of supply by only considering the mining stage and/or a country level does not provide a complete view of this mechanism. Illustratively, for the REE neodymium, Sprecher et al. (2017) found that the country-level concentration for the mining stage (i.e. REE mining) decreased over time, whereas the country-level concentration for the intermediate products stage (i.e. NdFeB magnets) worsened over time. Hence, computing the HHI for different stages in the supply chain can provide insight into which stage is least resilient from a diversity of supply perspective (Sprecher et al., 2017). Accordingly, several of the resilience studies have computed the country-level HHI for both the mining and refining stages (e.g., Galimberti, 2021; Van de Camp, 2020; Van den Brink et al., 2022).

In addition to distinguishing between the different supply chain stages, it is also important to distinguish between different levels of granularity when evaluating diversity of supply. As Sprecher et al. (2015) note in their original paper, Chinese attempts to acquire mines outside of China indicate that attention should not only be paid to the country in which a facility is located, but also to the facility's ownership. Accordingly, previous studies have also considered the company level in addition to the country level. For example, Sprecher et al. (2017) computed the company-level HHI for the intermediate products stage (i.e. NdFeB magnets). Van de Camp (2020) and Galimberti (2021) computed the company-level concentration based on refined material production volumes. Amongst the identified resilience studies, Van den Brink et al. (2022) analysed the diversity of supply mechanism in most detail. In terms of company-level concentration, the authors made a further distinction between the companies operating a facility and the parent companies (i.e. mining conglomerates). Moreover, the authors evaluated an additional level of granularity by computing the facility-level HHI for the individual mines and refineries (Van den Brink et al., 2022).

Besides production concentration, concentration of trade flows is also important to consider when analysing diversity of supply. After all, supply risk of mineral resources is intricately connected with global trade networks (Klimek et al., 2015). Therefore, Mancheri et al. (2018) analysed trade flows of unrefined tantalum and tantalum-containing intermediate products. Van den Brink et al. (2022) computed the country-level HHI based on trade flows of unrefined and refined antimony.

Regarding secondary supply, a further distinction can be made between pre-consumer and post-consumer recycling. Pre-consumer recycling, also called closed-loop recycling, is the reuse of materials lost during the manufacturing process and can therefore be viewed as a method to improve efficiency rather than to diversify supply (Cowley and Ryan, 2023; Mancheri et al., 2018; Sprecher et al., 2015). Post-consumer recycling, also called open-loop recycling, is the extraction of material from end-of-life (EOL) products (Cowley and Ryan, 2023). Post-consumer recycling does contribute to the diversity of supply by providing an alternative source of supply (Mancheri et al., 2018; Sprecher et al., 2015). Material criticality assessments often under-address recycling when evaluating a material's diversity of supply (Van den Brink et al., 2022). The identified resilience studies, by contrast, have typically evaluated recycling's contribution to supply by computing the fraction of total supply that comes from recycling (e.g., Galimberti, 2021; Mancheri et al., 2018; Van de Camp, 2020; Van den Brink et al., 2022).

Overall, it can be noted that previous analyses of the diversity of supply mechanism have primarily focussed on country-level and company-level production concentration for the mining and refining stages. Existent material criticality assessments and material supply chain resilience studies have generally under-explored the concentration of reserves, the facility-level production concentration, and the concentration of trade flows. Moreover, the studies that did analyse concentration of reserves (e.g. Mancheri et al., 2018), facility-level production concentration, and concentration of trade flows (Van den Brink et al., 2022), did not explore how these diversity of supply indicators can change over a period of multiple years.

2.5. The price mechanism

The price mechanism consists of several economic feedback loops that affect material supply and demand through the material price (Sprecher et al., 2015; Van den Brink et al., 2022). Disruptions can lead to a (perceived) market deficit, which in turn can lead to an increase in the price of a material (Sprecher et al., 2015; Van den Brink et al., 2022). This price increase can then affect the material's (future) supply and demand through the price feedback loops that make up the price mechanism. Six major price feedback loops can be identified (see Figure 2.1).

The first price feedback loop concerns the effect of the price of a material's co-mined metals on the material's primary supply. If a metal is mined together with other metals, its primary supply not only depends on the metal's own price, but also on the price of the metals with which it is co-mined (Sprecher et al., 2015; Van den Brink et al., 2022). More specifically, if a mine produces multiple metals, the mine's production is usually determined by the price and demand dynamics of the so-called host metal (Kim and Heo, 2012; Nassar et al., 2015; Van den Brink et al., 2022). The host metal is the metal that accounts for most of the mine's economic revenue and the other metals are referred to as companion metals (Nassar et al., 2015). If a metal is predominantly mined as a companion metal, its primary supply is likely to be inelastic (Nassar et al., 2015; Van den Brink et al., 2022). That is, the companion metal's mine production cannot easily be expanded in response to increases in its price or demand (Bustamante et al., 2018; Sprecher et al., 2017). Hence, it can be useful to investigate developments in the host metal market to gain insight into a companion's supply (Van de Camp, 2020). Moreover, it can be useful to compute the degree to which a metal is mined as a companion to other host metals, i.e. companionality (Nassar et al., 2015). Accordingly, Van den Brink et al. (2022) use companionality as an indicator for the price mechanism. Nassar et al. (2015) previously computed palladium's companionality for the year 2008, but did not investigate how palladium's companionality changed over time.

The second price feedback loop concerns the effect of a material's price on its primary supply. An increase in material price can incentivise investment in additional ore supply (Sprecher et al., 2015; Van den Brink et al., 2022). For example, a material price increase can lead to investment in exploration of new deposits (Castillo et al., 2023). To investigate the second price feedback loop for tantalum, Mancheri et al. (2018) provide a visual analysis of the correlation between the price and exploration budgets of nonferrous metals[3]. Moreover, a material price increase can also lead to investment in expansion of existing production capacity or opening new mines (Bustamante et al., 2018; Sprecher et al., 2015; Van de Camp, 2020). Sprecher et al. (2017) and Van de Camp (2020) investigate the relation between price and setting up new primary production capacity by conducting interviews. In terms of time delays, Van de Camp found that expanding the capacity of an existing mine can take 1.5-3 years and developing a new mine can take up to 7-10 years for cobalt. Similarly, for the REE neodymium, Sprecher et al. found a time lag of 1-13 years for expanding primary production. Compared to these resilience studies, Van den Brink et al. (2022) analyse the second price feedback loop more quantitatively by computing the Pearson correlation coefficient between antimony's price and primary production volumes per price cycle. A disadvantage of the Pearson correlation coefficient is that it provides limited information about the effect that price changes have on primary supply. That is, it only provides insight into the direction and strength of the linear relationship between price and primary supply.

The third price feedback loop concerns the effect of material price on secondary supply. An increase in material price can incentivise additional investment in recycling infrastructure (e.g. collection infrastructure or recycling production capacity), thereby raising secondary supply after a time delay (Sprecher et al., 2015; Van den Brink et al., 2022).

[3]The group of nonferrous metals is rather broad, which includes all alloys that do not contain a significant amount of iron.

The fourth price feedback loop concerns the effect of material price on stockpiles. An increase in material price can incentivise emergency stockpiling, thereby raising stockpiles (Sprecher et al., 2015; Van den Brink et al., 2022). Stockpiles can then either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). This price feedback loop is further discussed in the context of the stockpiling mechanism.

The fifth price feedback loop concerns the effect of material price on material demand through substitution. An increase in material price can incentivise additional investment in substitution R&D, thereby reducing material demand through increased substitution after a time delay (Sprecher et al., 2015; Van den Brink et al., 2022). Relatedly, the sixth price feedback loop concerns the effect of the price of a material's substitutes on material demand through substitution. If substitutes become less expensive relative to the material considered, this can incentivise increased substitution, thereby reducing demand (Nassar, 2015; Sprecher et al., 2015; Van den Brink et al., 2022). These final two price feedback loops are further discussed in the context of the substitution mechanism.

Overall, it can be noted that previous analyses of the price mechanism have primarily focused on the first two price feedback loops and have under-addressed the third price feedback loop. Moreover, previous material supply chain resilience studies have not provided a rigorous quantification of the first two price feedback loops. Furthermore, companionality has previously been identified as an important indicator for the first price feedback loop, but it has so far not been investigated how palladium's companionality can change over time.

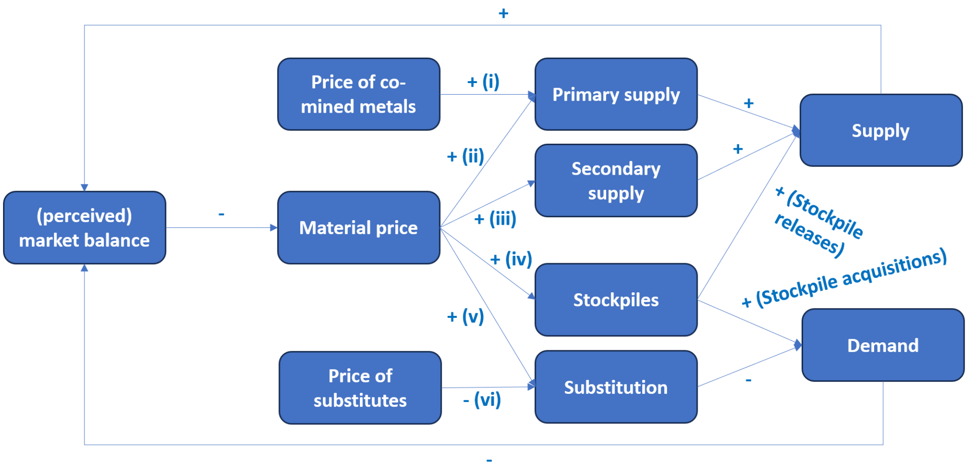

Figure 2.1: Conceptual model of the main price feedback loops in a material supply chain. Following System Dynamics convention, plus (+) and minus (-) signs between a factor A and factor B indicate that the factors move in the same direction or opposite direction, respectively (Bala et al., 2017). The six main price feedback loops are indicated by Roman numerals. Note that stockpiles can either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). Feedback loops (including their signs) are based on Sprecher et al. (2015) and Van den Brink et al. (2022, see supplement).

2.6. The stockpiling mechanism

The follow-up resilience studies have distinguished between three types of stockpiling actors: states, companies, and investors (Sprecher et al., 2015; Van de Camp, 2020). As shown in Figure 2.1 in the previous section, the stockpiling mechanism is governed by two competing feedback loops (Sprecher et al., 2015):

- The balancing feedback loop: releasing stockpiles creates an additional (postponed) source of supply. Therefore, stockpiles can act as a buffer when regular supply sources (i.e. primary and secondary) are temporarily disrupted. Since the stockpile releases enable the material supply chain system to maintain function (i.e. provide sufficient supply to satisfy societal demand) during a disruption, this dynamic positively affects resistance and thus resilience. This effect represents a balancing feedback loop, because stockpiles' buffering effect reduces the impact of supply disruptions.

- The reinforcing feedback loop: building stockpiles creates an additional source of demand. Therefore, when stockpiles are built during times of market deficit (i.e. speculative stockpiling), this can aggravate the existing market deficit. Since building stockpiles can hinder the ability of the material supply chain to satisfy societal demand, this dynamic negatively affects resilience. This effect represents a reinforcing feedback loop, because stockpile building can aggravate the market deficit.

Hence, the stockpiling mechanism can both positively and negatively affect resilience (Sprecher et al., 2015; Van den Brink et al., 2022). Stockpiling can improve resilience by absorbing sudden fluctuations in metal supply and prices (Sprecher et al., 2015). However, stockpiling can also diminish resilience by exacerbating supply shortages and price spikes (Sprecher et al., 2015; Van den Brink et al., 2022). This exacerbating effect can be unintended. For example, during the 2010 REE crisis, some Japanese companies forced their suppliers to stockpile neodymium when prices were high, which drove up prices even further (Sprecher et al., 2015). However, the exacerbating effect can also be intended, as financial speculators aim to benefit from price volatility (Sprecher et al., 2015). Accordingly, Van de Camp (2020) concluded that the relationship between stockpiling and resilience is ultimately contingent upon the strategy and position of the actor holding the stockpile.

Overall, the analyses of the stockpiling mechanism in the resilience studies tend to be very brief and are limited in two main ways. First, the studies mainly discuss strategic stockpiling by states and tend do under-address stockpiling by companies and especially investors. Second, the studies have used solely qualitative methods, i.e. literature reviews and interviews, rather than quantitative methods to analyse the stockpiling mechanism (e.g., see Galimberti, 2021; Mancheri et al., 2018; Sprecher et al., 2015; Van den Brink et al., 2022). The under-exploration of the stockpiling mechanism and the lack of quantitative evaluation methods can be explained by the fact that official data on stockpiling amounts is typically difficult to obtain. After all, holders of stockpiles are often reluctant to disclose such information for strategic purposes.

2.7. The substitution mechanism

A distinction can be made between two types of substitution: technological substitution and material substitution (Galimberti, 2021; Sprecher et al., 2015). Technological substitution concerns replacing the overall technology used in an end-product. An example of technological substitution in the case of palladium is replacing the internal combustion engine (ICE) with an electric traction motor in vehicles. Material substitution concerns replacing the material used in an end-product with an alternative substitute material. An example of material substitution in the case of palladium is replacing palladium with platinum in autocatalysts.

Material criticality assessment have used substitutability as an indicator for both the supply risk and vulnerability dimensions (Achzet and Helbig, 2013; Schrijvers et al., 2020). On the one hand, substitutability can be interpreted as a supply risk indicator: the availability of substitutes lowers the overall demand of a material, which makes the occurrence of a supply shortage less likely (Helbig et al., 2016). Substitutability can also be interpreted as a vulnerability indicator: the availability of substitutes allows producers to switch to alternative materials in case of a disruption, thereby limiting the economic impact of a disruption during the disruption. Criticality assessments have mostly evaluated substitutability qualitatively based on expert judgement, e.g. on a four- or five-point rating scale (Achzet and Helbig, 2013; Helbig et al., 2016). Consequently, the evaluation of substitutability is often opaque (Helbig et al., 2016).

Similarly, the follow-up resilience studies to the resilience framework by Sprecher et al. (2015) have primarily used qualitative literature review and interviews to evaluate the substitution mechanism. The potential of technological and material substitution was analysed for either one application (Mancheri et al., 2018; Sprecher et al., 2015, 2017; Van de Camp, 2020) or multiple applications (Galimberti, 2021; Van den Brink et al., 2022) of the material under consideration. The studies typically investigated whether substitutes exist for the selected application(s); how the substitutes compared to the material studied in terms of technical performance; and historic drivers of substitution. Improved technical performance of substitutes, material price increases, and changes in legislation (e.g. industry standards) were identified as incentives for substitution (Galimberti, 2021; Sprecher et al., 2015). Furthermore, the studies found that the substitution mechanism is characterised by time lags with the implementation of material substitution taking several months to several years depending on historic substitution R&D

and sector-specific regulations (Sprecher et al., 2015, 2017;Van den Brink et al., 2022).

The extent to which material substitution occurs depends on various considerations, including technical performance, material availability, environmental, and economic considerations (Nassar, 2015). Accordingly, Mancheri et al. (2018) found that a tantalum price decrease incentivised the use of tantalum as a substitute in capacitors, despite tantalum's inferior technical performance. The effects of material price and the price of substitutes on substitution are captured by the fifth and sixth price feedback loops (recall Figure 2.1).

Overall, it can be noted that criticality assessments and the follow-up resilience studies have primarily relied on qualitative methods to evaluate the substitution mechanism. In particular, previous material supply chain resilience studies have not provided a rigorous quantification of the fifth and sixth price feedback loops.

2.8. Overview of research gaps

Based on the above review of related material criticality and material supply chain resilience literature, the following research gaps are identified:

- Palladium has so far not been studied from a material supply chain resilience perspective. Studying CRMs from a resilience perspective is a relatively recent approach that accounts for several limitations of criticality assessments and requires further exploration (Dewulf et al., 2016; Schrijvers et al., 2020; Sprecher et al., 2015).
- The qualitative Sprecher et al. (2015) framework is a commonly used conceptualisation of material supply chain resilience (Castillo-Villagra and Thoben, 2022), but has so far not been quantitatively validated. The quantitative resilience metrics proposed by Sprecher et al. (2017) as an extension of the original framework are not very practical, because of the reliance on stakeholder interviews for data collection. This calls for an alternative approach to evaluate the resilience mechanisms that is less reliant on stakeholder interviews.
- The existing follow-up studies to the original Sprecher et al. (2015) framework have two major limitations. Firstly, they have not systematically explored how a material's resilience overall and the underlying factors that affect this resilience can change over time. In particular, the existent studies have not analysed how concentration of trade flows, facility-level production concentration, and companionality can change over time. Indeed, more research is required to investigate how resilience of material supply chains can change over time (Van den Brink et al., 2020). Secondly, these studies have mostly used qualitative methods (i.e. interviews and literature review) rather than quantitative methods to evaluate the resilience mechanisms. In particular, they have not provided a rigorous quantification of the price feedback loops.
- More research is needed to investigate the relative informativeness of the indicators used in material criticality assessments in terms of criticality and resilience. This could provide CRM researchers with more guidance regarding the selection of criticality assessment indicators. Moreover, this could provide policy-makers with more insight into the prioritisation of resilience-promoting strategies.

3
Methodology

This chapter outlines the methodology used in this study and describes the data sources used. The first section introduces the overall approach and the subsequent sections discuss the phases of the research approach in more detail.

3.1. Overall approach

This research follows a quantitative observational research approach that resembles a data science process. The key phases of a data science process include defining the problem, retrieving the data, preparing the data, exploring the data, analysing and modelling the data, and communicating the results (Baldassarre, 2016; Cielen and Meysman, 2016; O'Neil and Schutt, 2013). Note that the process of data preparation and exploration is iterative, as exploration of the data will indicate data quality issues that then need to be addressed in the data preparation (O'Neil and Schutt, 2013). Similarly, this study's approach comprises of six phases: problem definition, data retrieval, data preparation & exploration, data analysis & modelling, policy implications, and discussion & conclusions. The corresponding research flow diagram is shown in Figure 3.1.

In the first phase, i.e. the problem definition phase, the research question is defined in a rigorous way through system conceptualisation and operationalisation. Following Sprecher et al. (2015), the palladium supply chain is conceptualised as a system consisting of four interlinked resilience mechanisms. Subsequently, resilience and the resilience mechanisms are operationalised. In the second phase, i.e. the data retrieval phase, data related to the operationalised resilience and resilience mechanisms are collected. In the data preparation & exploration phase, the collected data are pre-processed and explored. These first three phases correspond to this Methodology chapter (Chapter 3) and the Operationalisation of Resilience Mechanisms chapter (Chapter 4). Then, in the data analysis & modelling phase, the evolution of the operationalised resilience mechanisms over time is analysed. The data analysis & modelling phase corresponds to the Diversity of Supply Mechanism, Price Mechanism, Stockpiling Mechanism, and Substitution Mechanism chapters (Chapters 5-8). In the policy implications phase, the implications of the findings from the data analysis & modelling phase for policy-makers are discussed. The policy implications phase corresponds to the Policy Implications chapter (Chapter 9). Finally, in the discussion & conclusions phase, this study's findings are summarised and their relevance and limitations are discussed. The conclusions phase corresponds to the Discussion and Conclusion chapters (Chapter 10-11).

This research uses Python and the Tableau Desktop software as data analysis tools. The data source and data analysis files used in this study are made publicly available in a Google Drive folder[1]. The following sections discuss the various phases in this study's research approach in more detail.

3.2. Problem definition phase

The first phase concerns defining the problem in a rigorous way. More specifically, this involves defining the system boundaries of the system under consideration and operationalising the research question.

[1] See https://drive.google.com/drive/folders/1wCprTfJGjo6QvgZBjBKBoIyDDmMUJCPG?usp=sharing

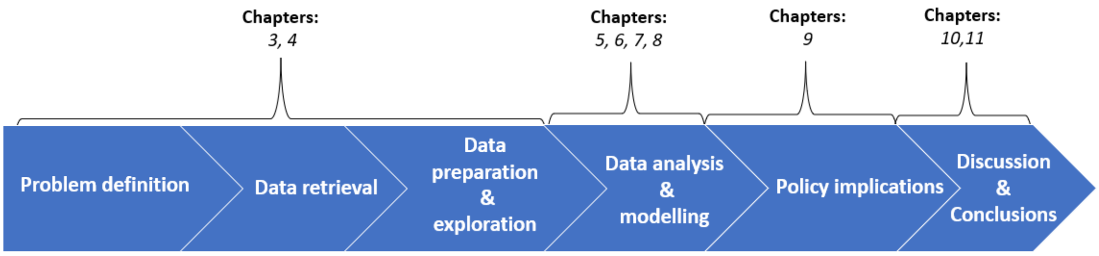

Figure 3.1: Research flow diagram visualising this study's research approach.

Recall that the main research question in this study is: *How has the palladium supply chain's resilience changed over time, and what challenges or opportunities does this imply for policy-makers?* Note that this research question contains the abstract notions of *the palladium supply chain* and *resilience*, which require further operationalisation. The following two subsections discuss the conceptualisation of the palladium supply chain and operationalisation of resilience used in this study.

3.2.1. Conceptualisation of the palladium supply chain

Material systems, such as the palladium supply chain system, are characterised by deep uncertainty (Kwakkel and Pruyt, 2015; Pruyt, 2010). That is, there is no consensus about which conceptual model provides the most appropriate representation of the system (Lempert et al., 2003). Indeed, as Van de Camp (2020) correctly pointed out, there is not *one* unambiguous supply chain in practice, but rather a multitude of supply chain actors with different conceptualisations of *the* supply chain in which they are involved. Hence, it is important to be explicit about the selected conceptualisation of the palladium supply chain system.

The overall supply chain of a final product containing palladium, e.g. electronics or internal combustion engine vehicles (ICEVs), can be conceptualised as having three system levels (cf. Sprecher et al. (2015)):

- System level 3 - Society: people having certain needs, such as the need for reducing pollutant emissions (i.e. the need for clean air).
- System level 2 - The production system: the system that converts processed palladium into palladium-containing products in order to meet the needs of society. For example, producing ICEVs with autocatalysts that reduce transport-related emissions. This system level involves producing intermediate products and assembling intermediate products into final products.
- System level 1 - The palladium supply chain: the system that provides processed palladium to the production system. This system level involves extraction and processing of palladium. Note that palladium can both be extracted from ores through mining or extracted from EOL palladium-containing products through recycling.

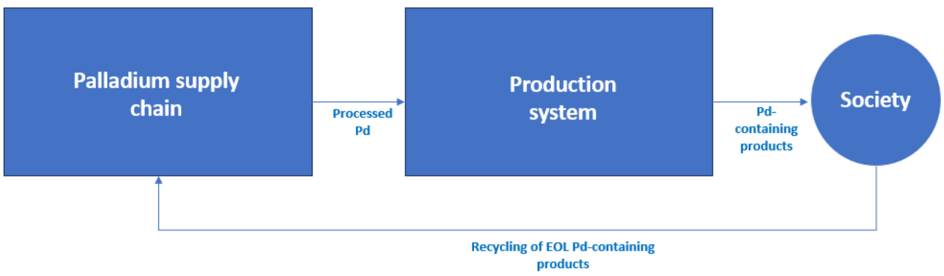

Figure 3.2: Conceptualisation of the supply chain of a final product containing palladium. System levels adapted from Sprecher et al. (2015). Palladium is abbreviated as Pd.

This overarching system is visualised in Figure 3.2. This study focuses on the first system level of this overarching system, i.e. the palladium supply chain, for two reasons. First, this material supply chain is a particularly relevant part of the overall product supply chain to consider in terms of resilience. After all, supply-side constraints mostly originate in the beginning of the product supply chain (Sprecher et al., 2015). Second, as opposed to focusing on the production of one final product in particular, investigating this first material part of the overall supply chain bears relevance for a wide range of final products containing palladium. In line with the above, the definition of the palladium supply chain used in this study is as follows:

- The palladium supply chain: *the material system that provides palladium required to meet the needs of society*.

Following Sprecher et al. (2015), the palladium supply chain is conceptualised as consisting of four interlinked resilience mechanisms: the diversity of supply, price, stockpiling, and substitution mechanisms. This study adopts this conceptualisation of material supply chains for three main reasons.

Firstly, this conceptualisation provides a global system perspective of the palladium supply chain. That is, the palladium supply chain is conceptualised as an interlinked system with the whole world as a geographical boundary. This is an appropriate conceptualisation of the palladium supply chain, because it is highly globalised with different stages of the supply chain (mining, processing, recycling) and actors spread across the globe (Georgitzikis et al., 2023). Taking such a global system perspective accounts for the limitation of several criticality assessments that study material supply chains only from a national or regional perspective (Lütkehaus et al., 2022; Schrijvers et al., 2020).

Secondly, this conceptual framework explicitly distinguishes between individual resilience mechanisms. This enables more in-depth analysis of the individual underlying mechanisms in the material supply chain compared to the aggregated scores typically provided by criticality assessments. This is particularly relevant to inform the formulation of risk-mitigating policies, as this study aims to do.

Thirdly, this conceptualisation explicitly incorporates recycling as part of the framework's diversity of supply resilience mechanism, whereas criticality assessments often under-address recycling as a source of material supply (Van den Brink et al., 2022).

In this study, the palladium supply chain is thus conceptualised as consisting of four interlinked sub-systems: the diversity of supply, price, stockpiling, and substitution mechanisms. Moreover, as an extension of the qualitative resilience framework by Sprecher et al. (2015), this study operationalises the four mechanisms in terms of a set of quantitative indicators and proxies. The reason for this operationalisation is threefold. First, such quantitative indicators and proxies enable systematic tracking of the evolution of the four mechanisms over time. This is particularly useful in the context of this study, which investigates the temporal dynamics of resilience. Second, these measurable indicators enable quantitative validation of the qualitative Sprecher et al. (2015) resilience framework. Sprecher et al. (2015) postulated that the four mechanisms are the primary drivers of resilience in material supply chains. However, review of the literature indicated that this has so far not been empirically established using quantitative indicators. Third, this quantification of the qualitative Sprecher et al. (2015) resilience framework is crucial to enable incorporation of resilience in material criticality assessments (Sprecher et al., 2017), as recommended by Dewulf et al. (2016).

The operationalisation of each of the four resilience mechanisms is discussed in Chapter 4. This Operationalisation of Resilience Mechanisms chapter thus relates to the first sub-question: *How can the four resilience mechanisms be operationalised, considering data availability and quality?*

3.2.2. Operationalisation of resilience

For systems in general, resilience refers to a system's ability to retain its function when exposed to disruptions (Fiksel, 2006; Meadows, 2008; Sprecher et al., 2015). The main function of a supply chain (system) is to satisfy customer's demand (Heckmann et al., 2015). Hence, the function of the palladium supply chain is to satisfy societal demand for palladium, particularly during disruptions.

For supply chains, resilience is typically defined as the ability of the supply chain to return to its original state or move to a more desirable state after a disruption (Heckmann et al., 2015; Ribeiro and Barbosa-Povoa, 2018). Arguably, the original state and/or the most desirable state is an equilibrium state in which supply and demand are balanced. Accordingly, the definition of resilience used in this study is as follows:

- Resilience: *the ability of the palladium supply chain to supply enough palladium to satisfy the demands of society*.

Note that this definition differs from the definition of material supply chain resilience proposed by Sprecher et al. (2015). Sprecher et al. defined material supply chain resilience as 'the capacity to supply enough of a given material to satisfy the demands of society, and to provide suitable alternatives if insufficient supply [compared to demand] is available' (2015, p. 6741). The second part of this definition is arguably already accounted for in the first part, as alternatives (e.g. substitute technologies or substitute materials) effectively reduce demand for the studied material. Moreover, the second part of this definition is arguably rather fuzzy and ill-suited for quantitative validation. Hence, this study only adopts the first part of this definition. That is, material supply chain resilience is defined as the ability of the material supply chain to provide sufficient supply to satisfy demand for a material.

It follows from the proposed definition of resilience that resilience is intrinsically dynamic. After all, both the demands of society and the ability of the supply chain to satisfy these demands can change over time.

Similar to the resilience mechanisms, the concept of palladium supply chain resilience requires operationalisation in terms of quantitative indicators for two reasons. First, this operationalisation of resilience enables systematically tracking the extent to which supply has historically satisfied demand. Second, the use of measurable indicators enables quantitative validation of the Sprecher et al. (2015) resilience framework. The palladium market balance, i.e. palladium supply minus palladium demand, is used as a performance indicator for the palladium supply chain's resilience. Considering that this study conceptualises the palladium supply chain as a global system, global palladium supply and demand are considered. A non-negative market balance indicates that global demand for palladium has been satisfied, thus indicating resilience. A negative market balance indicates that global demand exceeds global supply for palladium, thus indicating a lack of resilience.

3.3. Data retrieval and data preparation & exploration phases

The second phase in this study's research approach, i.e. the data retrieval phase, concerns collecting the data required to answer the research questions. Data is retrieved from a wide variety of public sources, including palladium recycling companies (Johnson Matthey), palladium mining companies (African Rainbow Minerals, Anglo American Platinum, Glencore, Impala Platinum, Norilsk Nickel, Zimplats), commodity research organisations (CPM group, SFA Oxford), financial data providers (Bloomberg, Macrotrends, Reuters), government agencies (DERA, JOGMEC, USGS), and the World Bank.

The third phase, i.e. the data preparation & exploration phase, concerns pre-processing and exploring the retrieved data to enable further analysis. This phase includes data cleaning tasks, such as treating missing values, as well as data transformation tasks, such as aggregating data, and merging data from different sources. The retrieval and preparation of the data sources related to the operationalised resilience mechanisms is discussed in the next chapter. This section discusses the retrieval and preparation of the supply and demand data as well as of the price data, which are used throughout the remainer of this study. More details regarding the data retrieval and preparation & exploration phases can be found in Appendix A.

3.3.1. Supply and demand data: Johnson Matthey dataset

To compute the market balance, annual global palladium supply and demand data are retrieved from the metals company Johnson Matthey (JM) (2023a). The dataset covers the years 1980-2023 and includes primary supply by region, secondary supply by application, and demand by region and application. Data for the year 2023 is not considered in this study, because this year is ongoing at the time of writing.

This study uses the supply and demand data by JM, thereby adopting the company's definitions of supply and demand (see Cowley and Ryan, 2023). This has implications for the operationalisation of resilience. Following Johnson Matthey, this study defines global palladium supply as primary supply plus secondary supply. Primary supply for a given year is defined as newly mined palladium sold by producers that year. Note that, for a given year, primary supply is not necessarily equivalent to underlying mine production in that year, because mining companies can also include sales from inventory (Cowley and Ryan, 2023). Secondary supply for a given year is defined as palladium recovered from post-consumer recycling[2] that is sold by producers that year. Similar to primary supply, secondary

[2]Recall from Chapter 2 that post-consumer recycling concerns extracting a material (palladium) by recycling EOL products after they have been used by consumers. Post-consumer recycling is also referred to as open-loop recycling, because the original industrial purchaser of the material does not retain ownership of the material, but the material is integrated in a final

supply for a given year is not necessarily equivalent to underlying recycling production in that year, because recycling companies can also include sales from inventory (Cowley and Ryan, 2023). Note that it is unfortunately not possible to distinguish between palladium directly derived from production and palladium sold from inventory, as companies do not explicitly report this.

Global palladium demand for a given year is defined as new palladium requirements in that year, after accounting for demand satisfied by inventory use and pre-consumer recycling[3] (Cowley and Ryan, 2023; Johnson Matthey, 2023b). Demand thus refers to gross demand prior to post-consumer recycling that can either be satisfied from primary or secondary supply (Johnson Matthey, 2023b).

3.3.2. Price data

At several moments in the remainder of this study, the annual real palladium price is used. For example, in visualisations and to estimate price elasticities. This annual real palladium price is computed as follows. First, daily nominal (spot) palladium prices in US dollars per troy ounce (oz) are retrieved from Macrotrends (2023). Subsequently, the annual nominal palladium price is obtained by averaging the daily nominal prices in a given year. Finally, to enable comparison of prices over time, the annual nominal price is adjusted for inflation using the Commodity Price Index [4] retrieved from the World Bank (2023b).

3.4. Data analysis & modelling phase

The data analysis & modelling phase (Chapters 5-8) adresses the second sub-question: *How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?* In this phase, the evolution of each of the four resilience mechanisms over time is investigated by performing a data analysis of the proxies identified per mechanism. To that end, a combination of historical data analysis, data visualisation, and regression modelling is used.

3.5. Policy implications phase

In the policy implications & discussion phase (Chapter 9), the implications of the findings from the data analysis & modelling phase for policy-makers are discussed. This phase corresponds to the final sub-question: *Given how the four resilience mechanisms have changed over time, what recommendations can be made to policy-makers to promote the palladium supply chain's resilience?*

To provide policy-makers with a clear overview of the temporal dynamics of resilience overall, the proxies per resilience mechanism analysed in the previous data analysis & modelling phase are synthesised into a single compound resilience index. Constructing such a compound resilience index involves two fundamental structural design choices: indicator selection and choosing an appropriate weighting scheme for the indicators. The set of indicators included in the resilience index is based on a selection of the proxies per resilience mechanisms identified in the Operationalisation of Resilience Mechanisms chapter (Chapter 4). Following Bulut and Thompson (2023), statistical-weighting based on Principal Component Analysis is selected as a weighting method. More details regarding the computation of the resilience index are discussed in the Policy Implications chapter (Chapter 9).

Furthermore, policy recommendations to improve the palladium supply chain's resilience are discussed based on the previous phase's analyses of the four resilience mechanisms.

3.6. Discussion & conclusions phases

In the final phase, this study's main findings are summarised and their validity and implications are discussed. More specifically, the Discussion chapter (Chapter 10) discusses the relevance of this study's findings and reflects on the validity and limitations of this study's approach. In the final Conclusions chapter (11), this study's main findings are summarised and the main research question is addressed: *How has the palladium supply chain's resilience changed over time, and what challenges or opportunities does this imply for policy-makers?*

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product that is then sold to another end-user (Cowley and Ryan, 2023). For example, palladium can be initially purchased by car companies, who then integrate it as autocatalyst in cars sold to consumers.

[3]Recall from Chapter 2 that pre-consumer recycling concerns extracting a material (palladium) by recycling waste generated during the industrial manufacturing or production process. Pre-consumer recycling is also referred to as closed-loop recycling, because ownership of the material is retained by the industrial user (Cowley and Ryan, 2023).

[4]The group of precious metals consists of gold, silver, and the PGMs.

4
Operationalisation of resilience mechanisms

In this chapter, the operationalisation of the four resilience mechanisms identified by Sprecher et al. (2015) is discussed. This chapter thus relates to the first sub-question: *How can the four resilience mechanisms be operationalised, considering data availability and quality?*

4.1. Introduction

The resilience framework by Sprecher et al. (2015) identifies four mechanism as the primary drivers of resilience in material supply chains: the diversity of supply, price, stockpiling, and substitution mechanisms (Van den Brink et al., 2022). Previous studies that have built on this resilience framework, have primarily evaluated each resilience mechanism through qualitative literature review and interview-based methods. This study, by contrast, operationalises each of the resilience mechanisms in terms of a set of quantitative indicators and proxies.

This operationalisation of the qualitative resilience framework by Sprecher et al. (2015) is used throughout the remainder of this study and is useful for three reasons. First, it enables systematically investigating the temporal dynamics of the resilience mechanisms. Accordingly, the operationalisation presented in this chapter is used in the next four chapters to investigate how the four resilience mechanisms have changed over time and how this has affected the palladium supply chain's resilience. Second, the operationalisation of the resilience mechanisms presented in this chapter enables quantitative validation of the Sprecher et al. (2015) framework. Accordingly, in Chapter 9, a selection of the indicators presented here is used to construct a compound resilience index and quantitively validate the Sprecher et al. (2015) framework. Third, the quantification of the resilience mechanisms is crucial to enable incorporation of the resilience concept in material criticality assessments (Sprecher et al., 2017).

The remainder of this chapter consists of five sections. Sections 4.2, 4.3, 4.4, and 4.5 discuss the operationalisation of the diversity of supply, price, stockpiling, and substitution mechanisms, respectively. For each resilience mechanism, a set of indicator and proxy variables is identified that measures the mechanism's resilience-promoting dynamics. The final section, Section 4.6, summarises this chapter's main findings and addresses the sub-question.

4.2. Operationalisation of the diversity of supply mechanism

The diversity of supply mechanism concerns the diversity of supply sources. More variety in the sources of supply can reduce the system's vulnerability to disruptions of individual suppliers (Sprecher et al., 2015). To evaluate the diversity of supply mechanism, a distinction can be made between primary supply, secondary supply, and ASM (Sprecher et al., 2015). However, similar to Sprecher et al. (2017), this study does not analyse ASM as a source of supply due to a lack of data. Moreover, palladium's association with ASM has been identified as 'low', indicating that ASM is relatively rare for palladium (Material Insights, 2023). Furthermore, the review of the existing literature indicated that distinctions can be made between concentration of reserves, production, and trade flows as well as between different stages of the supply chain (mining, refining), and between different levels of granularity (country, company, facility). Moreover, the literature overview indicated that material criticality assessments and previous material supply chain resilience studies have typically used the Herfindahl-Hirschman Index (HHI) as a proxy to measure concentration of production and trade flows (Schrijvers et al., 2020; Silberglitt et al., 2013; Van den Brink et al., 2022). Therefore, this study's operationalisation of the diversity of supply mechanism also uses the HHI as a proxy for concentration of production and trade flows.

Accordingly, this study operationalises the diversity of supply mechanism by considering four indicators: (i) the concentration of reserves, (ii) the concentration of primary production, (iii) recycling's contribution to meeting demand, and (iv) the concentration of trade flows.

The first indicator is the concentration of reserves[1]. This indicator relates to primary supply, because primary supply originates from mining these reserves. As a sub-indicator, the country-level concentration of reserves is considered. This sub-indicator provides insight into where (future) primary production can occur and indicates whether geographic diversification is possible (Castillo et al., 2023; Rietveld et al., 2022). To the best of the author's knowledge, data on reserves of palladium specifically are not readily available. However, palladium typically occurs in deposits together with other PGMs (Encyclopaedia Britannica, 2023; Gunn and Benham, 2009). Hence, the country-level HHI of PGM reserves is computed as a proxy. To that end, estimates of PGM reserves per country are retrieved from USGS Mineral Commodity Summaries (2006, 2007, 2008, 1998, 1999a, 2000, 2001, 2002, 2003, 2004, 2005, 2009, 2010, 2011, 2012, 2013, 2014a, 2015a, 2016, 2017, 2018, 1996, 1997, 2020, 2021, 2022, 2023, 2019), which is a commonly used data source for global reserves estimates (Mudd et al., 2018).

The second indicator is the supplier concentration of primary production. This indicator relates to primary supply. Unfortunately, in line with the latest EU criticality assessment (European Commission, 2023c), this study does not distinguish between the mining and refining stages of palladium production. The reason for this is that available production data does not provide sufficient detail to distinguish between the production volumes of the mining and refining stages, but only reports the eventual refined production (European Commission, 2023c; JRC, 2023b)[2]. However, a distinction is made between three levels of granularity, resulting in three sub-indicators: country-level, facility-level, and company-level concentration of primary production. On a country-level, the country-level HHI of primary palladium production is computed as a proxy. To that end, the production per country is retrieved from DERA (2020) and the USGS (Schulte, 2022, 2023). On a facility-level, the facility-level HHI of primary palladium production is computed as a proxy. To that end, palladium production volumes per mining facility are retrieved from Buchholz et al. (2022), JOGMEC (2013, 2014, 2015, 2017a, 2017b, 2018, 2019, 2021, 2022a, 2022b, 2023a, 2023b, 2023c), and reports by palladium mining companies African Rainbow Minerals (2019), Anglo American Platinum (2016, 2018, 2019, 2021, 2023), Glencore (2016, 2017, 2019), Impala Platinum (2012, 2016, 2020, 2022), Norilsk Nickel (2011, 2022), and Zimplats (2019)[3]. On a company-level, the company-level HHI of primary palladium production is used as a proxy. To that end, market shares of the largest palladium mining companies are retrieved from annual reports by Norilsk Nickel (2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023a).

The third indicator is recycling's contribution to meeting palladium demand. This indicator relates to secondary supply and measures the importance of recycling as a source of supply. The end-of-life recycling input rate (EOL-RIR) is used as a sub-indicator. Indeed, the 'EOL-RIR [$\cdots$] is regarded as a robust measure of recycling's contribution to meeting materials demand' (Talens Peiro et al., 2018, p. 2). The EOL-RIR is defined as the share of overall material demand that is satisfied through secondary supply (European Commission, 2023c). As a proxy, this study computes the share of global secondary palladium supply in global palladium demand. Following the methodology used by the EU's Joint Research Centre (JRC, 2023b), this involves dividing total secondary supply by gross demand as reported by Johnson Matthey (2023a). Following previous resilience studies (Mancheri et al., 2018; Sprecher et al., 2015), only post-consumer recycling is considered as part of the diversity of supply

[1]Recall from Chapter 2 that reserves are the deposits of a material that are economically feasible to mine (Rietveld et al., 2022).

[2]Mining companies report the production volumes of metallurgically produced palladium or palladium payable (European Commission, 2023c; JRC, 2023b).

[3]For details, see the excel file *production_per_mine.xlsx* in the shared Google Drive.

mechanism, as opposed to pre-consumer recycling[4]. The rationale behind this is that pre-consumer recycling can be viewed as a an efficiency-improving practice rather than as a diversification of supply (Cowley and Ryan, 2023; Mancheri et al., 2018; Sprecher et al., 2015).

The fourth and final indicator is the supplier concentration of trade flows. Considering this study's scope[5], two types of trade flows are considered relevant: PGM ores and concentrates as well as refined palladium. However, this study does not consider trade flows of PGM ores and concentrates for two reasons. First, international trade statistics do not provide sufficient detail to separate trade flows of PGM ores and concentrates from trade flows of other precious metals (Georgitzikis et al., 2023; JRC, 2023b)[6]. Second, PGMs are typically traded in the form of refined metals and the trade of ores and concentrates is very limited (European Commission, 2023c). This can be explained by the fact that PGM mining and processing operations are typically integrated at or near the mine site (European Commission, 2023c; Gunn and Benham, 2009), as transportation of unrefined PGMs over long distances is unpractical and/or uneconomical. Hence, this study focuses on trade flows of refined palladium only. Accordingly, the country-level concentration of refined palladium trade flows is considered as a sub-indicator. As a proxy, the country-level HHI of net exports of refined palladium is used. This proxy is computed based on net exports of 'palladium, unwrought or in powder form' (HS711021), which are retrieved from the United Nations Commodity Trade Statistics Database (UN Comtrade, 2023).

An overview of the indicators, sub-indicators, proxy variables, and data sources used to operationalise the diversity of supply mechanism is provided in Table 4.1. More information on the retrieval and preparation of the corresponding data sources can be found in Appendix A.3.

Indicator	Sub-indicator	Proxy	Data sources
Concentration of reserves	Country-level concentration of reserves	Country-level HHI of PGM reserves	USGS (1996-2023)
Concentration of primary production	Country-level concentration of primary production	Country-level HHI of primary palladium production	DERA (2020)
			USGS (2022)
			USGS (2023)
	Facility-level concentration of primary production	Facility-level HHI of primary palladium production	Buchholz et al. (2022)
			JOGMEC (2013-2023)
			Company publications
	Company-level concentration of primary production	Company-level HHI of primary palladium production	Norilsk Nickel (2011-2023)
Recycling's contribution to meeting demand	EOL-RIR	Share of secondary supply in demand	Johnson Matthey (2023a)
Concentration of trade flows	Country-level concentration of refined palladium trade flows	Country-level HHI of net exports of HS711021	UN Comtrade (2023)

Table 4.1: Overview of the operationalisation of the diversity of supply mechanism.

4.3. Operationalisation of the price mechanism

The price mechanism consists of the economic feedback loops through which the price affects material supply and demand (Sprecher et al., 2015). Recall from Chapter 2 that six main feedback loops through the price mechanism can be identified. These price feedback loops are visualised in Figure 4.1. The remainder of this study explores how the signs and magnitudes of these price feedback loops have changed over time. More specifically, following Van den Brink et al. (2022), the first three price feedback

[4] Note that the secondary supply data retrieved from Johnson Matthey (2023a) indeed only includes post-consumer recycling and not pre-consumer recycling (Cowley and Ryan, 2023).

[5] Recall from the methodology chapter that this study focuses on the palladium material system rather than on the production system of palladium-containing products. Hence, trade flows of intermediate palladium-containing products are beyond the scope of this study.

[6] The HS nomenclature used by UN Comtrade (2023) does not provide sufficient detail to analyse trade flows of PGM ores and concentrates (JRC, 2023b).

loops are discussed as part of the analysis of the price mechanism. The fourth price feedback loop is discussed as part of the analysis of the stockpiling mechanism. The fifth and sixth price feedback loops are discussed as part of the analysis of the substitution mechanism. Indeed, Figure 4.1 illustrates that the price feedback loops link the various resilience mechanisms together (Sprecher et al., 2015; Van den Brink et al., 2022).

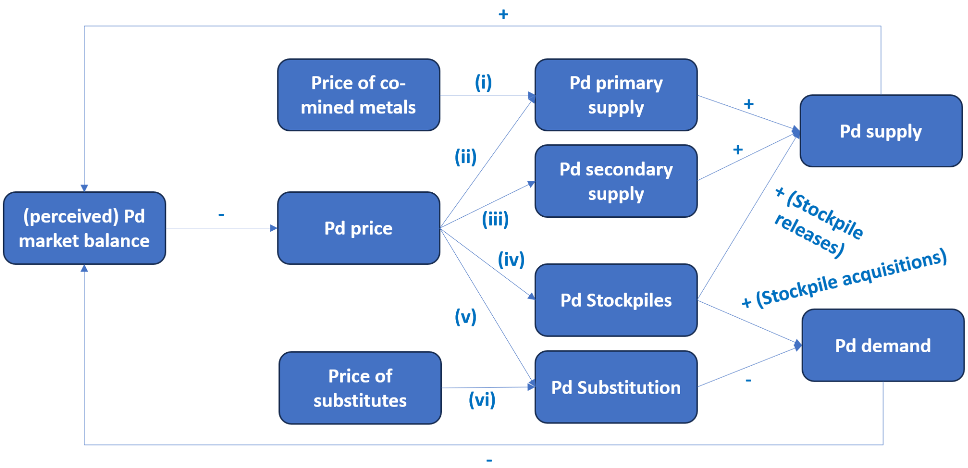

Figure 4.1: Conceptual model of the main price feedback loops in the palladium supply chain. Following System Dynamics convention, plus (+) and minus (-) signs between a factor A and factor B indicate that the factors move in the same direction or opposite direction, respectively (Bala et al., 2017). Pd refers to palladium. The six main price feedback loops are indicated by Roman numerals. Their signs and magnitudes are explored in the remainder of this study. Note that stockpiles can either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). Feedback loops based on Sprecher et al. (2015) and Van den Brink et al. (2022, see supplement).

This operationalisation of the price mechanism thus focuses on the first three price feedback loops. Recall from Chapter 2 that the first price feedback loop concerns the effect of the price of a material's co-mined metals on the material's primary supply. Indeed, palladium's primary supply is affected by the prices of the metals with which it is co-mined (Nassar et al., 2015; SFA Oxford, 2023d). The literature review indicated that if a metal is predominantly mined as a companion metal[7], its primary supply is likely to be inelastic (Nassar et al., 2015; Van den Brink et al., 2022). This implies that the responsiveness of primary palladium supply both to changes in the palladium price and changes in the price of co-mined metals depends on the degree to which palladium is mined as a companion to other host metals. That is, the magnitude of the first two price feedback loops depends on palladium's companionality.

Moreover, recall that the second price feedback loop concerns the effect of a material's price on its primary supply. Previous studies argued that a material price increase can incentivise investment in additional production capacity, thereby raising primary supply after a time delay (Bustamante et al., 2018; Sprecher et al., 2015; Van den Brink et al., 2022). Lastly, recall that the third price feedback loop concerns the effect of material price on secondary supply. Previous studies argued that a material price increase can incentivise additional investment in recycling infrastructure (e.g. collection infrastructure or recycling production capacity), thereby raising secondary supply after a time delay (Sprecher et al., 2015; Van den Brink et al., 2022).

Accordingly, this study operationalises the price mechanism by considering three indicators: (i) companionality, (ii) the price elasticity of supply, and (iii) the cross price elasticity of supply.

As argued above, the first indicator, i.e. palladium's companionality, relates to the first two price feedback loops. Accordingly, Van den Brink et al. (2022) previously used companionality as an indicator for the price mechanism. Companionality can be measured by computing the share of primary production in which the metal is mined as a companion (Nassar et al., 2015). Hence, as a proxy for the first indicator, the share of primary palladium production in which palladium is mined as a companion is computed based on a selection of palladium mines globally. To that end, mine-level palladium produc-

[7] Recall from Chapter 2 a host is the metal that accounts for most of a mine's economic revenue and companions are the remaining co-mined metals (Nassar et al., 2015).

tion volumes and revenue contributions by metal are retrieved from Buchholz et al. (2022), JOGMEC (2013-2023), and company publications (Anglo American Platinum, Impala Platinum, Norilsk Nickel, Zimplats)[8].

The second indicator, i.e. the price elasticity of palladium supply, is defined as the percent change in palladium supply divided by the percent change in the palladium price. Material supply is considered relatively inelastic if the supply increases at a smaller rate than the metal price increases (University of Minnesota, 2016). That is, the price elasticity of supply ranges between 0 and 1. Conversely, material supply is considered relatively elastic if the supply increases at a greater rate than the metal price increases (University of Minnesota, 2016). That is, the price elasticity of demand is larger than 1. A relatively elastic supply implies that the price mechanism's supply-raising, i.e. resilience-promoting, ability is relatively strong. The price elasticity of supply is a particularly relevant indicator for the price mechanism, because it quantifies the direction and magnitude of the second and third price feedback loops.

The third indicator, i.e. the cross price elasticity of palladium supply, is defined as the percent change in palladium supply divided by the percent change in the price of another material. The cross price elasticity of supply is a particularly relevant indicator for the price mechanism, because it quantifies the first price feedback loop.

Price elasticities are commonly estimated by using a log-log linear regression model (Holmes et al., 2017). Accordingly, the regression-estimated price elasticity of supply and cross price elasticity of supply are used as proxies for the second and third indicator, respectively. To that end, logged palladium supply is regressed on logged (real) palladium price and logged (real) price of three metals with which palladium is co-mined. Palladium is typically mined together with copper, nickel, and platinum (DeCarlo and Goodman, 2022; SFA Oxford, 2023d). Accordingly, metal price data is retrieved for copper, nickel, and platinum. Palladium supply data is retrieved from Johnson Matthey (2023a). To account for time lags, not only the prices in the same year as supply, but also the time-lagged prices are considered as explanatory variables. Time lags of 1-10 years are considered, because expanding primary supply can take up to 10 years (Van de Camp, 2020). Nominal palladium prices as well as copper, nickel, and platinum prices are retrieved from Macrotrends (2023) and the World Bank (2023b), respectively. Subsequently, these nominal prices are adjusted for inflation based on the Commodity Price Index (World Bank, 2023b).

An overview of the indicators, proxy variables, and data sources used to operationalise the price mechanism is provided in Table 4.2.

Indicator	**Proxy**	**Data sources**
Companionality	Share of primary palladium production where palladium is a companion	Buchholz et al. (2022)
		JOGMEC (2013-2023)
		Company publications
Price elasticity of supply	Regression-estimated price elasticity of supply	Johnson Matthey (2023a)
		Macrotrends (2023)
		World Bank (2023b)
Cross price elasticity of supply	Regression-estimated cross price elasticity of supply	Johnson Matthey (2023a)
		World Bank (2023b)

Table 4.2: Overview of the operationalisation of the price mechanism.

4.4. Operationalisation of the stockpiling mechanism

The stockpiling mechanism concerns the build-up of stockpiles of a material for future use. Stockpiling can both promote and reduce resilience (Sprecher et al., 2015; Van den Brink et al., 2022). On the one hand, stockpiles can act as a buffer when regular supply sources (i.e. primary and secondary) are temporarily disrupted, as stockpile releases create an additional source of supply (Sprecher et al., 2015). On the other hand, speculative stockpile acquisitions can aggravate market deficits by raising demand (Sprecher et al., 2015). Accordingly, Figure 4.1 shows that palladium stockpiles can both raise supply through stockpile releases and raise demand through stockpile acquisitions.

[8]For details, see the excel files *production_per_mine.xlsx* and *metal_revenue_by_mine.xlsx* in the shared Google Drive.

This study operationalises the stockpiling mechanism by considering two indicators: (i) the time palladium stockpiles can satisfy societal palladium demand when regular supply sources are disrupted and (ii) stockpile allocations.

The first indicator measures the potential of stockpiles to act as a buffer during temporary supply disruptions. Sprecher et al. (2017) suggest that stockpiling can be quantified by considering the number of months a material supply chain can sustain itself when supply is disrupted. Accordingly, the first indicator used to operationalise the stockpiling mechanism is the time in months palladium stockpiles can satisfy palladium demand when regular supply sources are disrupted. Of course, the time stockpiles can satisfy demand during a period of supply disruption depends on the extent to which supply is disrupted. The indicator considered in this study quantifies the time in months that palladium stockpiles can satisfy societal palladium demand if primary and secondary supply are assumed to be completely disrupted. The indicator thus reflects the maximum magnitude of the buffering effect of the stockpiling mechanism. The first indicator is therefore similar to the maximum magnitude resilience metric proposed by Sprecher et al. (2017). Since official statistics of stockpile sizes are typically undisclosed for strategic purposes, a proxy variable is used to approximate this indicator: the estimated size of total stockpiles, expressed in months of demand. To that end, global palladium demand estimates are retrieved from Johnson Matthey (2023a) and estimates of the size of total stockpiles are retrieved from Bloomberg (Mazneva and Pakiam, 2020) and Reuters (Hobson and Harvey, 2023; Patel and Shivaprasad, 2023). In addition to being used for the first indicator, the stockpile size estimates are also used to quantify the relationship between palladium price and total palladium stockpiles, i.e. the fourth price feedback loop in Figure 4.1.

Only considering the first indicator, however, does not provide a complete view of the stockpiling mechanism. At first glance, a large stockpile might seem desirable from a resilience perspective due to its large potential to act as a buffer during supply disruptions. However, if this stockpile is built during years of market deficits, building the stockpile itself may have aggravated market deficits, thereby negatively affecting resilience in the process. Therefore, it is also relevant to consider the timing of stockpile allocations, i.e. stockpile releases or acquisitions. Hence, stockpile allocations are used as a second indicator of the stockpiling mechanism. Similar to stockpile sizes, stockpile allocations are typically undisclosed by stockpile owners for strategic purposes, resulting in an (intentional) data gap regarding stockpile allocations. Therefore, a proxy variable is used to approximate this indicator: estimated identifiable stockpile allocations. Estimates of stockpile allocations are identified for three types of stockpiling actors: states, companies in the supply chain, and investors. These estimates are retrieved from the USGS (George, 2004, 2005; Hilliard, 1999b; Reese, 1994), Johnson Matthey (2023a), Reuters (Alexander et al., 2019; O'Connell et al., 2015), and SFA Oxford (2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023d).

An overview of the indicators, proxy variables, and data sources used to operationalise the stockpiling mechanism is provided in Table 4.3.

Indicator	Proxy	Data sources
Time stockpiles can satisfy demand when regular supply sources are disrupted	Estimated size of stockpiles expressed in months of demand	Bloomberg (2020)
		Reuters (2023)
		Johnson Matthey (2023a)
Stockpile allocations	Estimated identifiable stockpile allocations	USGS (2004, 2005, 1999b, 1994)
		Johnson Matthey (2023a)
		Reuters (2019, 2015)
		SFA Oxford (2016-2023)

Table 4.3: Overview of the operationalisation of the stockpiling mechanism.

4.5. Operationalisation of the substitution mechanism

The substitution mechanism concerns substitution either of the overall technology used in an end-product or of the material used (Sprecher et al., 2015). Substitution contributes to resilience by lowering the overall demand for a material (Sprecher et al., 2015). After all, the availability of suitable substitutes allows producers to use alternatives, thereby making the occurrence of a market deficit less likely

(Duclos et al., 2010; Helbig et al., 2016; Schrijvers et al., 2020).

In contrast to the qualitative approaches to substitutability often used in criticality assessments (Achzet and Helbig, 2013; Helbig et al., 2016), price elasticity of demand and cross price elasticity of demand can be used as quantitative indicators for substitution (Nassar, 2015). A material's price elasticity of demand measures the responsiveness of material demand to changes in material price. This responsiveness depends on the extent to which substitution occurs. Indeed, the price elasticity of demand reflects the availability of substitutes and the willingness of producers to use substitutes based on technical performance, economic, and other considerations (Nassar, 2015). A material's cross price elasticity of demand measures the responsiveness of material demand to changes in another material's price. This responsiveness to price changes of another material depends on the extent to which the other material is used as a substitute or complement (Fizaine, 2022; Nassar, 2015).

In line with the above, this study operationalises the substitution mechanism by considering two indicators: (i) the price elasticity of demand and (ii) the cross price elasticity of demand.

The first indicator, i.e. the price elasticity of demand, is defined as the percent change in palladium demand divided by the percent change in the palladium price. Material demand is considered relatively elastic if the demand decreases at a greater rate than the metal price increases (Nassar, 2015). That is, the price elasticity of demand is more negative than -1. Conversely, material demand is considered relatively inelastic if the demand decreases at a smaller rate than the metal price increases (Nassar, 2015). That is, the price elasticity of demand ranges between 0 and -1. Relatively inelastic demand implies limited substitution historically, suggesting a lack of suitable substitutes (Nassar, 2015). Conversely, relatively elastic demand implies frequent substitution historically, suggesting that suitable substitutes are available (Nassar, 2015). The first indicator thus quantifies the fifth price feedback loop in Figure 4.1.

The second indicator, i.e. the cross price elasticity of demand, is defined as the percent change in palladium demand divided by the percent change in the price of another material. Positive and negative cross-price elasticities imply that these other materials are substitutes and complements to palladium, respectively (Fizaine, 2022; Nassar, 2015). The second indicator thus quantifies the sixth price feedback loop in Figure 4.1.

Price elasticities are commonly estimated by using a log-log linear regression model (Holmes et al., 2017). Accordingly, the regression-estimated price elasticity of demand and cross price elasticity of demand are used as proxies for the first and second indicator, respectively. To that end, logged palladium demand is regressed on logged (real) palladium price and logged (real) price of palladium's substitutes. Metal price data is retrieved for four substitutes of palladium identified by Nassar (2015): platinum, nickel, gold, and silver. Palladium demand data is retrieved from Johnson Matthey (2023a). Nominal palladium prices as well as platinum, nickel, gold, and silver prices are retrieved from Macrotrends (2023) and the World Bank (2023b), respectively. Subsequently, these nominal prices are adjusted for inflation based on the Commodity Price Index (World Bank, 2023b).

An overview of the indicators, proxy variables, and data sources used to operationalise the substitution mechanism is provided in Table 4.4.

Indicator	Proxy	Data sources
Price elasticity of demand	Regression-estimated price elasticity of demand	Johnson Matthey (2023a)
		Macrotrends (2023)
		World Bank (2023b)
Cross price elasticity of demand	Regression-estimated cross price elasticity of demand	Johnson Matthey (2023a)
		World Bank (2023b)

Table 4.4: Overview of the operationalisation of the substitution mechanism.

4.6. Chapter conclusion

This chapter investigated how the four resilience mechanisms identified by Sprecher et al. (2015) could be operationalised, considering data availability and quality. To that end, each of the four resilience mechanisms were operationalised in terms of a set of quantitative indicators, sub-indicators, and proxies.

The diversity of supply mechanism is operationalised by considering four indicators: the concentration of reserves, the concentration of primary production, recycling's contribution to meeting demand, and the concentration of trade flows.

The price mechanism is operationalised by considering three indicators: companionality, the price elasticity of supply, and the cross price elasticity of supply.

The stockpiling mechanism is operationalised by considering two indicators: the time palladium stockpiles can satisfy societal palladium demand when regular supply sources are disrupted and stockpile allocations.

The substitution mechanism is operationalised by considering two indicators: the price elasticity of demand and the cross price elasticity of demand.

5
The diversity of supply mechanism

In this chapter, it is investigated how the diversity of supply mechanism has changed over time and how this has affected the palladium supply chain's resilience. This chapter relates to the second sub-question: *How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?*

5.1. Introduction

The diversity of supply mechanism concerns the diversity of supply sources. More variety in the sources of supply can reduce the system's vulnerability to disruptions of individual suppliers (Sprecher et al., 2015). To investigate the temporal dynamics of the diversity of supply mechanism, the diversity of supply mechanism was operationalised in Chapter 4 based on four indicators: (i) the concentration of reserves, (ii) the concentration of primary production, (iii) recycling's contribution to meeting demand, and (iv) the concentration of trade flows. An overview of this operationalisation of the diversity of supply mechanism is provided in Table 5.1.

Indicator	**Sub-indicator**	**Proxy**	**Data sources**
Concentration of reserves	Country-level concentration of reserves	Country-level HHI of PGM reserves	USGS (1996-2023)
Concentration of primary production	Country-level concentration of primary production	Country-level HHI of primary palladium production	DERA (2020) USGS (2022) USGS (2023)
	Facility-level concentration of primary production	Facility-level HHI of primary palladium production	Buchholz et al. (2022) JOGMEC (2013-2023) Company publications
	Company-level concentration of primary production	Company-level HHI of primary palladium production	Norilsk Nickel (2011-2023)
Recycling's contribution to meeting demand	EOL-RIR	Share of secondary supply in demand	Johnson Matthey (2023a)
Concentration of trade flows	Country-level concentration of refined palladium trade flows	Country-level HHI of net exports of HS711021	UN Comtrade (2023)

Table 5.1: Overview of the operationalisation of the diversity of supply mechanism.

The first section of this chapter discusses the concentration of reserves. Subsequently, the second section discusses the concentration of primary production, distinguishing between the country, company, and facility levels. The third section then discusses the contribution of recycling as a source of supply. The fourth section discusses the concentration of trade flows. The final section summarises this chapter's findings.

5.2. Concentration of reserves

This section discusses the first indicator of the diversity of supply mechanism, i.e. the concentration of reserves. In terms of terminology, note that resources are deposits of a mineral that are of sufficient quality and quantity to be of economic interest (Hughes et al., 2021). Reserves concern the part of the resource that is economically feasible to mine under present market conditions (Hughes et al., 2021; Rietveld et al., 2022). Estimates of resources and reserves can change over time due to the identification of new mineral deposits. Additionally, they can change as a result of technological advancements in extraction and processing or changing market conditions, which make previously uneconomical deposits economically viable to mine (Hughes et al., 2021; Rietveld et al., 2022).

In 2019, global PGM resources and reserves were estimated to amount to more than 100,000 metric tonnes and 69,310 metric tonnes, respectively (Singerling, 2019). Hughes et al. (2021) estimated that palladium accounted for approximately 35% of these total PGM reserves. Comparing this palladium reserves estimate to global primary supply in 2019 (Johnson Matthey, 2023a), palladium reserves account for approximately 110 years of primary supply. This finding confirms that there is no geological risk to the palladium supply as a result of resource depletion in the short term, unless demand drastically increases (Hughes et al., 2021; Mudd, 2012; Mudd et al., 2018).

The concentration of reserves, however, may pose a risk to the palladium supply. To evaluate how the country-level concentration of PGM reserves has evolved over time, the country-level Herfindahl-Hirschman Index (HHI) of PGM reserves is computed as a proxy. To that end, PGM reserves estimates per country are retrieved for the period 1996-2023 from the USGS (1996-2023). The country-level HHI per period is shown in Table 5.2. As can be expected, the computed country-level HHI of PGM reserves is in line with other studies that used USGS data. For example, Rietveld et al. (2022) also found an HHI of 8167 for the year 2022. Based on Table 5.2, it can be noted that the country-level HHI of reserves has remained relatively steady in the last 28 years with the HHI being constant during several periods. Considering the underlying reserves estimates per country, the changes in the HHI are primarily driven by changes in the estimated Russian PGM reserves.

For example, it can be noted that the HHI increased significantly between 2010 and 2011. Considering the underlying reserves estimates per country, this higher HHI reflects that PGM reserves became even more concentrated in South Africa, as estimated Russian reserves declined. More specifically, estimated Russian reserves decreased significantly from 6200 to 1100 metric tonnes between 2010 and 2011 (USGS, 2010, 2011). This can likely be explained by a decline in PGM ore grades of the Russian reserves in the preceding years (Piskulov, 2012)[1]. The lower PGM ore-grades reduced the fraction of deposits that was economically viable to mine, thereby effectively reducing reserves. Conversely, the HHI decreased significantly in 2017, 2018, 2022, and 2023 due to significant increases in estimated Russian reserves. The increase in estimated Russian reserves since 2017 can arguably primarily be explained by the relatively high PGM prices (especially palladium) in these years. After all, higher PGM prices can cause a larger fraction of deposits to become economically viable to mine (e.g. the deposits with relatively low ore-grades), thereby effectively raising reserves.

While estimated reserves for Russia thus changed over time, estimated reserves for other countries remained relatively steady. In fact, South African and Canadian PGM reserves are estimated to have remained constant since 1999 at 63,000 and 310 metric tonnes, respectively. Similarly, US PGM reserves are estimated to have remained constant at 900 metric tonnes since 2003.

It must be noted, however, that the USGS estimates of PGM reserves are uncertain, both because of the uncertainty involved in mineral exploration projects and because identified reserves have not always been publicly disclosed. In particular, Russian PGM reserves were confidential under Russian law until 2004 (George, 2005). Given this uncertainty, it is not surprising that the PGM reserves estimated by the USGS are not always consistent with other studies on PGM reserves. For example, Mudd et al. (2018) estimated 2015 South African PGM reserves at 10,790.3 metric tons compared to the 63,000 metric tons estimated by the USGS. The difference in estimated reserves can be explained by the fact that the USGS estimates are based on national reporting rather than company reporting of reserves (Mudd et al., 2018). For comparison, I compute the country-level HHI for the year 2015 based on the PGM reserves estimates per country reported by Mudd et al. (2018). This results in an HHI for the year 2015 of 4735 compared to 9088 based on USGS estimates. Unfortunately, the study by Mudd et al. (2018)

[1]Lower PGM ore grades indicate a lower quality of the PGM-containing ore. This implies that less PGM can be extracted from the same amount of ore.

Period	Country-level HHI of PGM reserves
1996-1997	7960
1998	7999
1999-2000	7965
2001	7950
2002	7756
2003-2010	7906
2011-2016	9088
2017	8980
2018-2021	8299
2022	8167
2023	7958

Table 5.2: Country-level Herfindahl-Hirschman Index of PGM reserves for the years 1996-2023. Note that the HHI ranges between 0 (no concentration) and 10,000 (monopoly). Own calculation based on PGM reserves estimates per country from USGS PGM Mineral Commodity Summaries (1996-2023).

does not provide sufficient information to compute the country-level HHI of reserves for years other than 2015. Clearly, more research into the evolution of country-level PGM reserves over time is needed to reliably analyse the annual changes in the country-level HHI of PGM reserves. Rietveld et al. (2022) concur that, for CRMs in general, data availability of resources and reserves requires improvement.

Nevertheless, several conclusions regarding the country-level concentration of PGM reserves can safely be discerned. Both the HHI computed for the years 1996-2023 based on estimates by the USGS and the HHI computed for the year 2015 based on Mudd et al. (2018) are significantly larger than 2500. This indicates a very high level of concentration (Silberglitt et al., 2013; Van den Brink et al., 2022). Hence, it is found that PGM reserves have consistently been highly concentrated during the years 1996-2023. Accordingly, based on the USGS estimates, South Africa and Russia together accounted for approximately 96-99% of global PGM reserves in the years 1996-2023. Indeed, PGM resources and reserves are widely recognised to be highly concentrated in Russia, Canada, the US, Zimbabwe, and primarily South Africa (Hughes et al., 2021; Mudd, 2012; Mudd et al., 2018). The world's largest PGM resources and reserves are found in the Bushveld Complex in South Africa, which is a basin-shaped igneous intrusion of approximately 380 kilometres across (Schulte, 2023; SFA Oxford, 2023a) (see Figure B.1 in Appendix B). Considering that mined palladium is ultimately derived from these reserves, these findings suggest that palladium mining is likely to remain highly concentrated in these five countries in the foreseeable future.

5.3. Concentration of primary production

This section discusses the second indicator, i.e. the concentration of primary production. Unfortunately, as argued in Chapter 4, no distinction can be made between the various palladium processing stages (mining, concentration, smelting, refining). The reason for this is that mining companies only report production volumes of refined palladium per mine (European Commission, 2023c; JRC, 2023b). This refined palladium output reported by mining companies is almost identical to underlying mine production (JRC, 2023b). Accordingly, the term ‘mine production’ in this chapter refers to refined palladium output derived from mining, as opposed to refined palladium output derived from recycling.

This study does make a distinction between three levels of granularity where concentration of production can occur: the country, facility, and company level. Accordingly, the following three subsections discuss how the concentration of palladium primary production has evolved over time on a country, facility, and company level.

5.3.1. Country level

The first sub-indicator that is considered to investigate the concentration of primary production is the country-level concentration of primary production. The country level is relevant to consider, because supply disruptions can occur as a result of events or policy decisions on a national level. For example, there is the risk of Russia restricting palladium exports on a national level (Hook and Dempsey, 2023; Teer and Bertolini, 2022).

To investigate how the country-level concentration of primary production has evolved over time, the country-level HHI of primary production is used as a proxy. To that end, annual palladium mine production per country is retrieved for the years 1964-2019 and 2020-2022 from DERA (2020) and USGS PGM Mineral Commodity Summaries (Schulte, 2022, 2023), respectively. For a given year, these country-level production volumes are then summed to obtain the annual global palladium mine production. Subsequently, countries' market shares in global palladium mine production and the overall country-level HHI are computed. Figure 5.1 shows the country-level HHI of palladium mine production for the years 1964-2022.

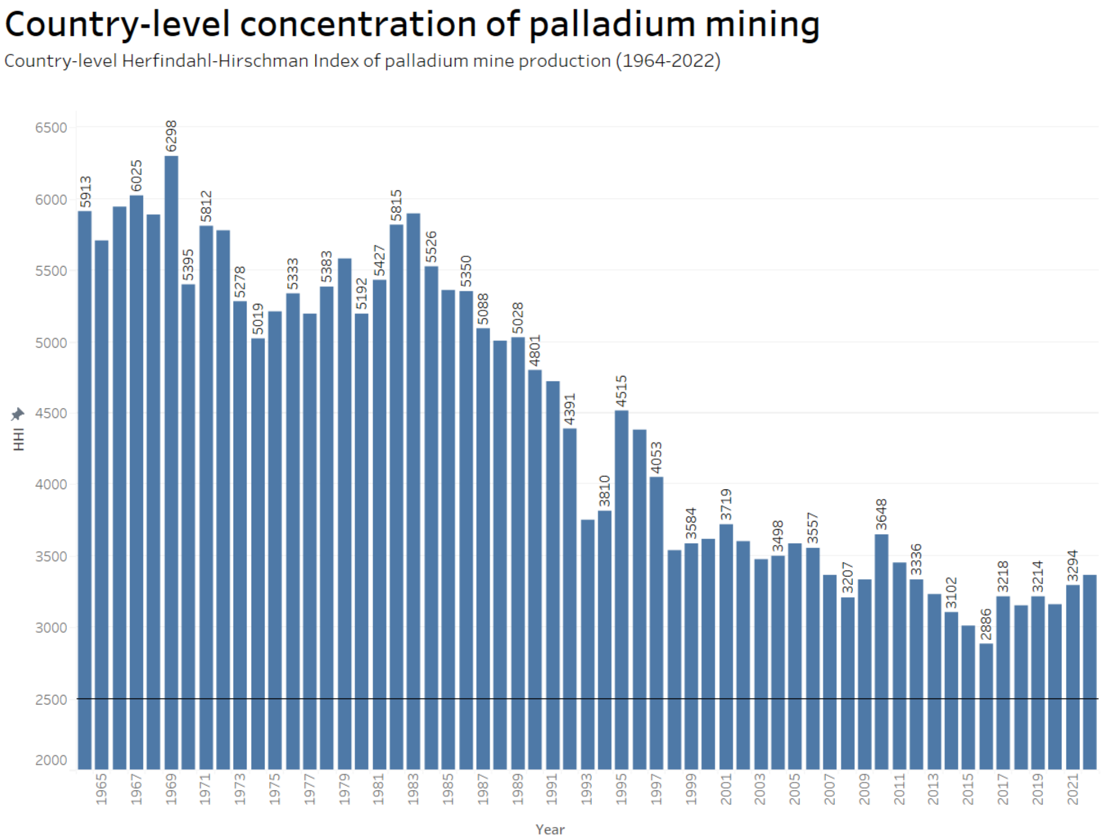

Figure 5.1: Country-level Herfindahl Hirschman Index (HHI) of palladium mine production for the years 1964-2022. Note that the HHI ranges between 0-10,000 and values above 2500 indicate a highly concentrated market. Figure based on own calculations using country-level mine production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

Based on this figure, it can be noted that the HHI has been significantly higher than 2500 for all years during the period 1964-2022, with a median HHI value of 4391. Such HHI values above 2500 indicate a highly concentrated market (Silberglitt et al., 2013; Van den Brink et al., 2022). Hence, the palladium mine production has consistently been highly concentrated during the years 1964-2022. In large part, the high concentration of primary palladium production can be explained by the high concentration of PGM reserves, which physically determine where palladium mining can occur. For reference, even if palladium mine production would be evenly distributed amongst the five main palladium-rich countries (South Africa, Russia, Canada, USA, Zimbabwe), this would still result in an HHI of 2000. Such a HHI value would still correspond to a moderately concentrated market (Silberglitt et al., 2013; Van den Brink et al., 2022). The mine production has, however, not been evenly distributed at all, resulting in very high HHI values. Figure 5.2 shows the Russian and South African market shares in global mine production for the years 1964-2022.

It can be noted that Russia and South Africa have historically dominated and continue to dominate palladium mine production. In the period 1964-2022, the combined market share of Russia and South Africa ranged between approximately 74% in and 95%, with a median value of 88%. Until the 1990s,

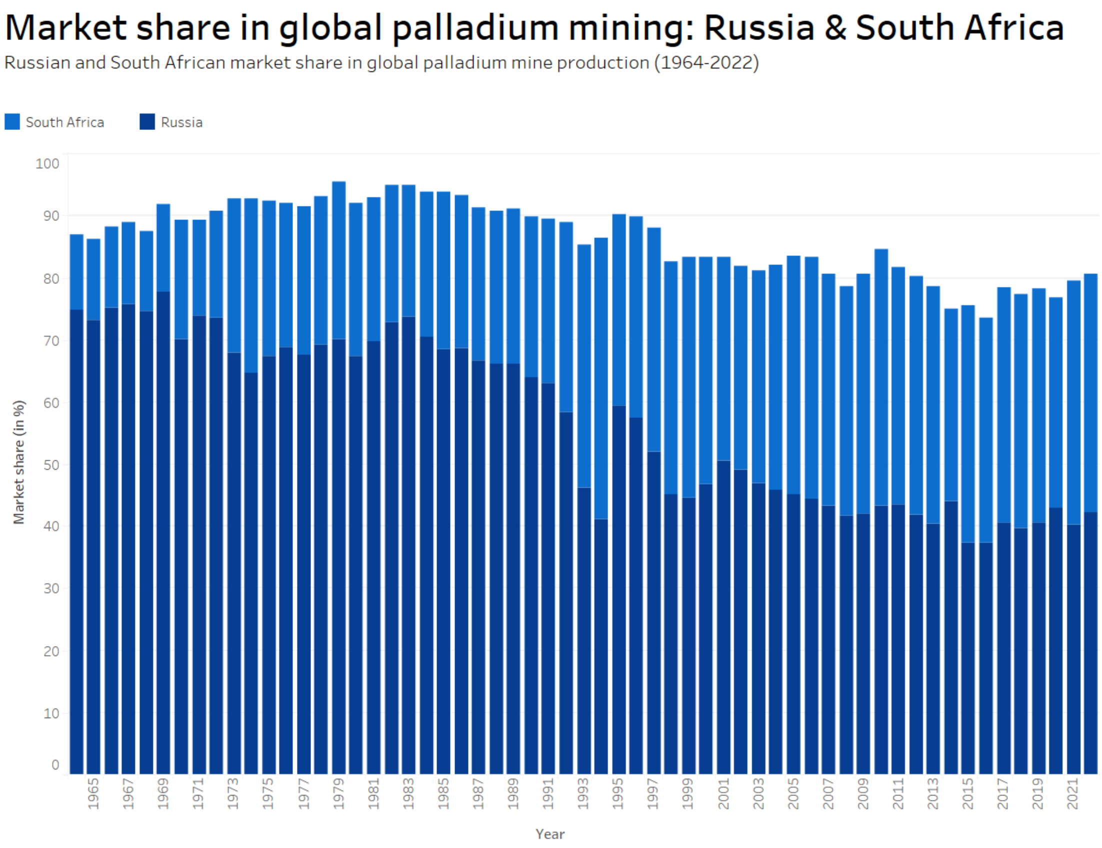

Figure 5.2: Russian and South African market share in global palladium mine production during the years 1964-2022. Figure based on own calculations using country-level mine production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

Russia (Soviet Union) was by far the largest palladium miner. In the 1960s, Russia accounted for as much as three quarters of global palladium mine production. Since then, the Russian market share has significantly decreased, but it only first dropped below 50% in 1993. In 2022, Russia still accounted for approximately 42% of global palladium mine production. This finding is in line with other recent studies that reported that Russia currently accounts for more than 40% of global palladium mine production (Carrara et al., 2023; Georgitzikis et al., 2023). Conversely, the South African market share more than tripled during the years 1964-2022, increasing from approximately 12% in 1964 to approximately 38% in 2022. Since 1990, South Africa has accounted for more than a quarter of global palladium mine production and this share continues to increase. Despite the convergence between the Russian and South African market shares over time, South Africa only surpassed Russia as the world's largest palladium miner in 1994 and 2015.

In addition to highlighting the consistently high level of concentration in palladium mining, Figure 5.1 also indicates that the country-level HHI has significantly decreased over time. More specifically, the country-level HHI declined by approximately 43% from 5913 in 1964 to 3368 in 2022. Considering the underlying market shares of individual countries, the decline in the HHI can primarily be explained by the fact that Russia has become less dominant in palladium mine production over time. Russia's market share decreased by 44% from approximately 75% in 1964 to approximately 42% in 2022. This decline in Russia's market share over time is primarily attributable to two developments.

The first development that contributed to the decline in the Russian market share is the significant increase in South African palladium mine production. Figure 5.3 shows Russian and South African palladium mine production during the years 1964-2022. It can be noted that, in line with global palladium production, both Russian and South African mine production significantly increased over time, but have been relatively steady in recent years. In relative terms, however, South African mine production increased much more than Russian mine production. Between 1964 and 2022, mine production

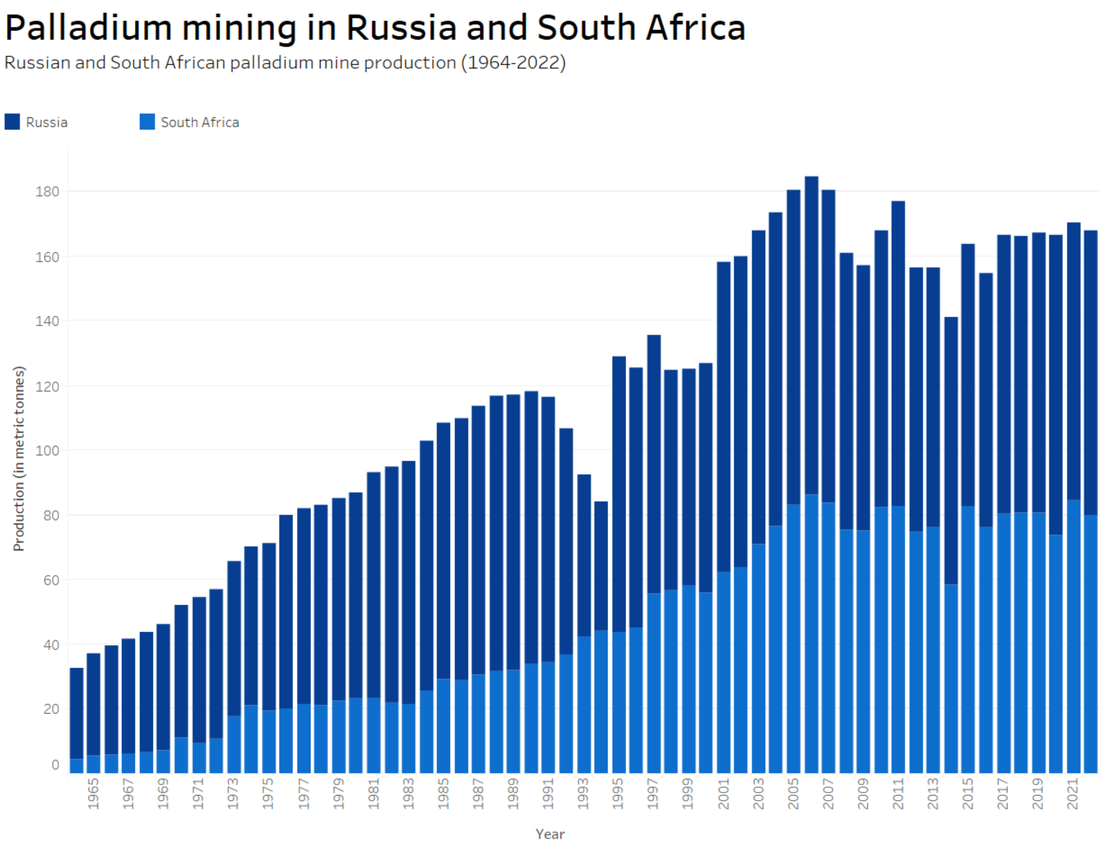

Figure 5.3: Russian and South African palladium mine production in metric tonnes during the years 1964-2022. Figure based on own calculations using country-level mine production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

increased by approximately 1674% and 214% for South Africa and Russia, respectively.

The second development that contributed to the decline in the Russian market share is an overall increase in palladium mine production outside Russia and South Africa. Figure 5.4 shows the market shares of countries other than Russia and South Africa during the years 1964-2022. The figure indicates that mine production outside Russia and South Africa increased by approximately 49% from 13% 1964 to 19% in 2022. In particular, it can be noted that Canada has historically been the most important palladium producer after Russia and South Africa, with a median market share of approximately 6%. Moreover, the USA and Zimbabwe have become noteworthy palladium miners since 1987 and 2003, respectively. Production has also occurred in several other countries, including Australia, Botswana, Poland, Finland, and former Yugoslavia. However the contribution to global production of countries other than Russia, South Africa, Canada, USA, and Zimbabwe has been negligibly small, with a median market share of approximately 0.2% during the years 1964-2022.

Overall, the analysis above indicates that palladium mine production has historically been highly concentrated in Canada, the USA, Zimbabwe, and especially Russia and South Africa. This is problematic from a diversity of supply point of view. Moreover, this high concentration is problematic from a resilience perspective, because it makes the ability to satisfy palladium demand vulnerable to supply disruptions in a handful of countries. This vulnerability is also illustrated by recent examples of (anticipated) supply disruptions in South Africa and Russia. For example, workers strikes in the South African mining sector significantly impacted global primary palladium production in 2014 (Stoddard, 2014). Similarly, in an effort to slow the spread of the COVID-19 virus, the closure of the South African mining sector for multiple weeks in 2020 significantly impacted global palladium supply and contributed to a palladium price spike (Buchholz et al., 2022; Christensen, 2020). Regarding Russia, speculation that Western sanctions in response to Russia's invasion of Ukraine could include an unprecedented ban on palladium from Russia contributed to significantly higher palladium price levels in 2022 (Dareen,

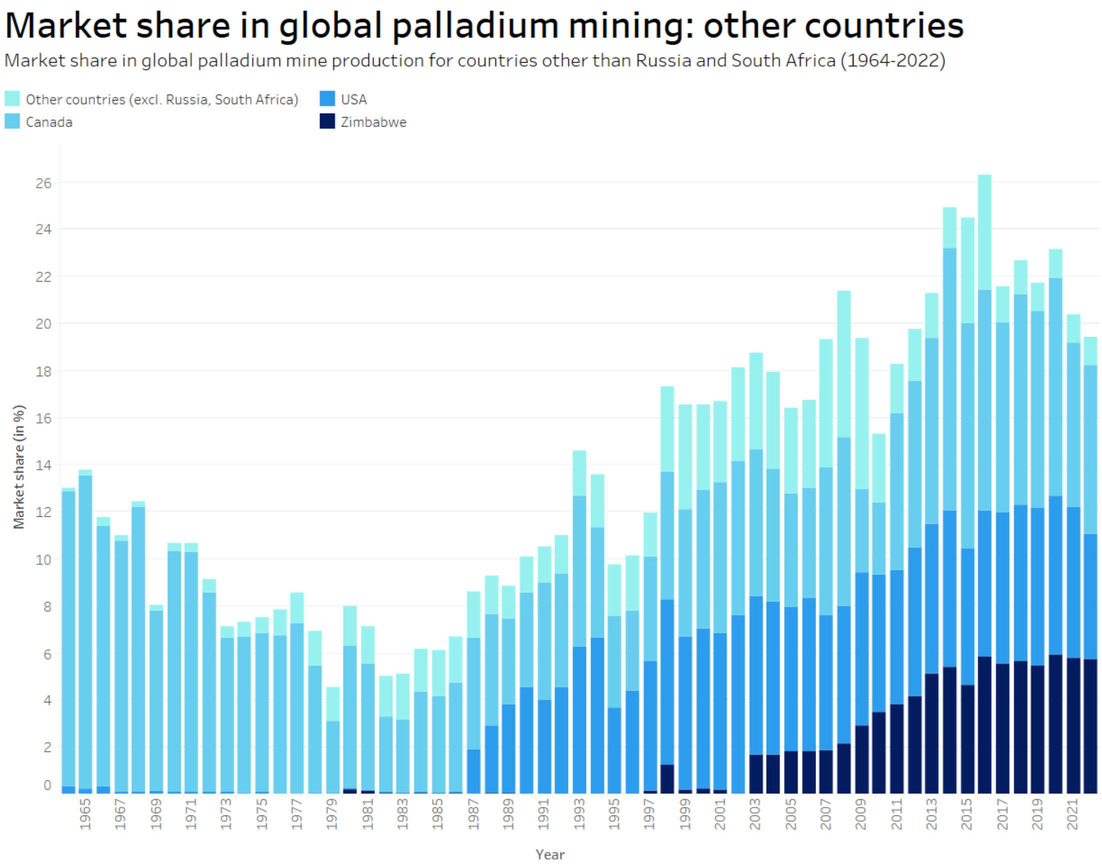

Figure 5.4: Market share in global palladium mine production for countries other than Russia and South Africa during the years 1964-2022. Figure based on own calculations using country-level mine production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

2022; SFA Oxford, 2022). Although palladium mine production remains highly concentrated, the observed decline in the country-level HHI of production since 1964 does indicate that palladium's diversity of primary supply has improved over time. In particular, Russia's dominance in global palladium mine production has decreased significantly over time, thereby making global primary palladium supply less vulnerable to Russian supply disruptions.

5.3.2. Facility level

The second sub-indicator that is considered to investigate the concentration of primary production is the facility-level primary production concentration. To explore how the facility-level concentration of primary production has evolved over time, the facility-level HHI of palladium primary production is used as a proxy. For the year 2018, Buchholz et al. (2022) identified 20 palladium mines and reported their production, which accounted for 87.4% of global primary production in that year. This dataset was used as a starting point. Since this study focuses on how production concentration evolves over time, additional data sources were consulted to identify mines and their production volumes for years other than 2018. In addition to Buchholz et al. (2022), annual production data per mine is therefore also retrieved from JOGMEC Global Mining Trends reports (2013-2023), and company publications (including African Rainbow Minerals, Anglo American Platinum, Impala Platinum, Glencore, Norilsk Nickel, and Zimplats). The process of manually retrieving the annual production data per mine was found to be extremely time-consuming, for example because the JOGMEC reports are only available in Japanese (see Appendix A.3). Therefore, production data per mine is only retrieved for the years 2012-2021 and primarily for mines in the countries Russia and South Africa. The rationale behind selecting the years 2012-2021 is that these most recent years are deemed to best reflect the current mine-level production concentration. The reason for primarily focusing on mines in Russia and South Africa is that the country-level production data indicated that Russia and South Africa have historically been the largest palladium producers, implying that the mines in these countries account for most of the global palladium production. For more details regarding the data retrieval and preparation process, see Appendix A.3.

In total, 42 distinct mining facilities are identified for which palladium production is reported in at least one year during the period 2012-2021. In order to compute a mine's annual market share in global palladium mine production, the annual global palladium mine production computed in the previous section is used again. For the years 2012-2021, the identified mine-level production volumes in total account for approximately 70.4%-88.4% of annual global palladium mine production, with a median coverage of 76.0%. In particular, note that this study slightly improves on the coverage of global palladium mine production for the year 2018 by Buchholz et al. (2022) due to the identification of additional mines: 88.4% compared to 87.4%. An overview of the number of identified mine production volumes and their coverage of global palladium mine production per year can be found in Table B.1 in Appendix B.

To account for the mine production not covered by the identified mines, lower and upper bounds are computed for the facility-level HHI[2]. The lower bound for the HHI is obtained by assuming the individual market shares of the non-identified mines are negligibly small (i.e. 0) and therefore do not contribute to the HHI. The upper bound for the HHI is obtained by assuming the production not covered by the identified mines derives from a single entity (mine), i.e. the unknown market shares of the non-identified mines are effectively merged. Table 5.3 shows the lower and upper bounds of the facility-level HHI for the years 2012-2021.

Table 5.3 shows that all computed upper bounds for the facility-level HHI are smaller than 2500, indicating a low-to-moderate concentration of primary palladium production on a facility level (Silberglitt et al., 2013; Van den Brink et al., 2022). It is interesting to note that in 2018, i.e. the year with the highest coverage of global production, the facility-level HHI ranges between 984 and 1120. This indicates that global palladium mining is not concentrated in 2018 in terms of the number of distinct mining facilities. Overall, no clear change in the facility-level HHI over time is apparent from Table 5.3. Possibly, the facility-level HHI did not change significantly during the years 2012-2021. However, this cannot be directly established from Table 5.3 due to the unknown market shares of the non-identified mines. What can be established is that, during the years 2012-2021, global palladium mining was not highly concentrated, but rather quite diversified or at worst moderately concentrated, in terms of the number of distinct mining facilities. This is desirable from a diversity of supply and resilience perspective, as it implies that a potential disruptive event at a single mine has a limited impact on global palladium primary supply.

To investigate the facility-level primary production concentration more extensively, concentration of mining facilities in Russia and South Africa are considered in more detail below. These two countries in particular are considered for two reasons. First, Russia and South Africa were identified as the world's largest primary producers of palladium in the previous subsection. Second, most of the identified mines are located in these countries.

[2] Recall that the theoretical lower and upper bounds are 0 and 10,000, respectively.

Year	Lower bound: facility-level HHI	Upper bound: facility-level HHI	Level of concentration
2012	1263	1482	Low
2013	1198	1426	Low
2014	1347	1758	Low/Medium
2015	964	1839	Low/Medium
2016	916	1456	Low
2017	974	1639	Low/Medium
2018	984	1120	Low
2019	1062	1816	Low/Medium
2020	958	1606	Low/Medium
2021	870	1486	Low

Table 5.3: Lower and upper bound of the facility-level HHI for the years 2012-2021. Note that the HHI ranges between 0 (no concentration) and 10,000 (monopoly). Table based on own calculations. Underlying facility-level production data retrieved from Buchholz et al. (2022), JOGMEC, and company reports. Underlying global production based on country-level production data from DERA (2020) and the USGS (Schulte, 2022, 2023). Level of concentration based on thresholds by Silberglitt et al. (2013) and Van den Brink et al. (2022).

For Russia, only two palladium mining facilities are identified: the Kola Division (also referred to as Kola MMC) and the Polar Division (also referred to as the Norilsk Division) (Buchholz et al., 2022). Recall from the previous subsection that Russia is the largest palladium miner globally, with an average market share of 40.5% during the years 2012-2021. The Russian palladium production seems to be completely attributable to just these two mining facilities. For example, in 2021, the identified production of the Kola Division and Polar Division mining facilities together accounted for approximately 93.6% of Russian mine production as reported by the USGS (Schulte, 2023). The remaining difference can likely be explained by differences in reporting, such as rounding and units of measurement[3]. This indicates that palladium mining within Russia is extremely concentrated on a facility level. Moreover, both mining facilities are owned by Russian mining company Norilsk Nickel (2023a), which implies that palladium mining within Russia is monopolised by a single mining company. Figure 5.5 shows the market share in global mining production for the Kola Division and Polar Division mining facilities during the years 2012-2021.

It can be noted that, during the years 2012-2021, the market share of the Kola Division doubled due to increased production, whereas the market share of the Polar Division halved due to decreased production. Moreover, it can be noted that the combined market share of the two mining facilities remained relatively steady during these years. Together, the Kola Division and Polar Division mining facilities consistently accounted for approximately 40% of global palladium mine production in the period 2012-2021. This indicates that the Kola Division and Polar Division mining facilities have been integral to Russian palladium mine production and global palladium mine production in general, during the years 2012-2021.

In contrast to Russian palladium mining, palladium mining in South Africa seems fairly diversified on a facility level. Figure 5.6 shows the market shares in global palladium mine production for identified South African mines during the years 2012-2021. For visual purposes, only the top 10 mines in terms of market share are shown.

Based on Figure 5.6, it can be noted that the market shares of individual South African mines remained relatively modest during the years 2012-2021, especially compared to the Russian mines. Still, the contributions of the Mogalakwena and Impala mines to global palladium mining are not insignificant. The market share of the Mogalakwena mine increased from approximately 5.2% in 2012 to 8.2% in 2021. The market share of the Impala mine decreased from 6.5% in 2012 to 5.0% in 2021. Although palladium mining in South Africa is diverse in terms of distinct mining facilities, it is more concentrated if one considers the ownership or geographic location of the mines. Table 5.4 shows the shareholders and location for the same top 10 South African mines shown in Figure 5.6.

In terms of ownership, it can be noted that a small number of mining companies jointly owns these top 10 mines, including Anglo American Platinum Ltd., Impala Platinum Holdings Ltd., Sibanye-

[3]For example, Norilsk Nickel (2022) reports the production amounts per mine in koz, while the USGS (Schulte, 2023) reports total Russian production in kg.

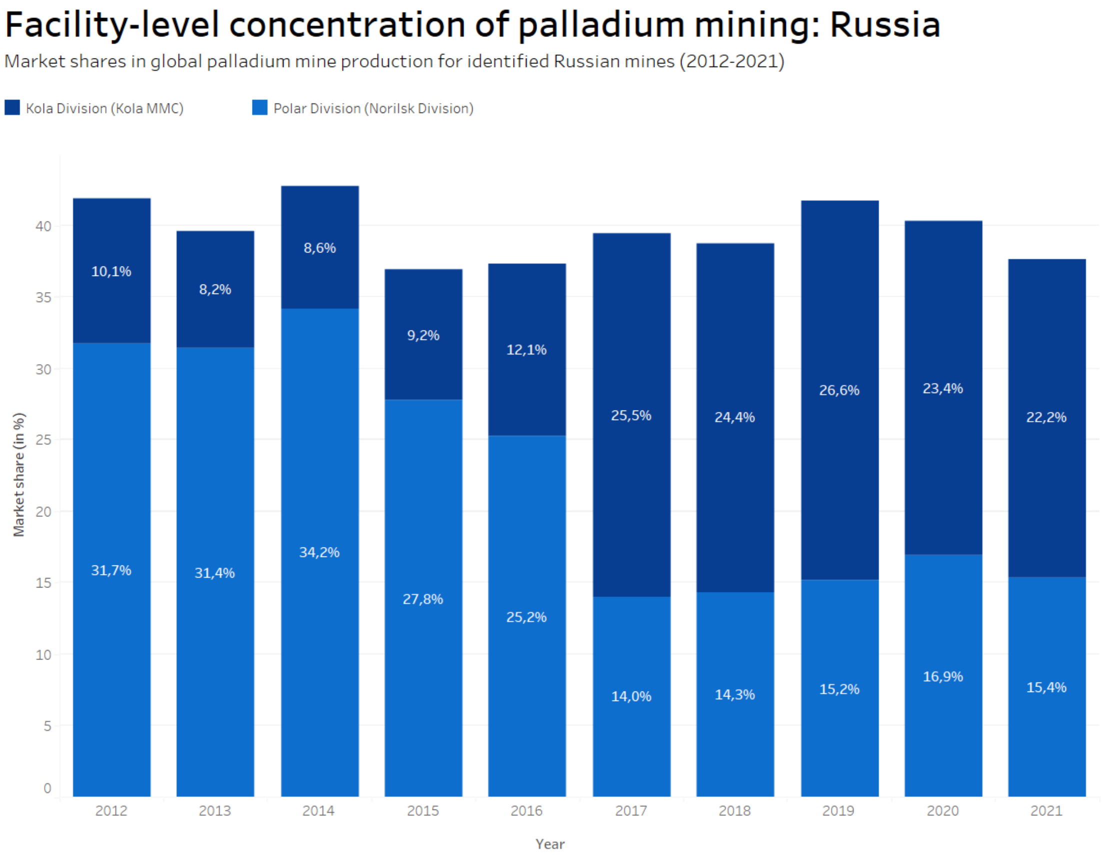

Figure 5.5: Market shares in global palladium mine production for identified Russian mines during the years 2012-2021. Figure based on own calculations. Underlying facility-level production data retrieved from Norilsk Nickel (2022). Underlying global production based on country-level production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

Stillwater Ltd., and African Rainbow Minerals Ltd. In particular, half of the top 10 mines is (partially) owned by Anglo American Platinum Ltd. In terms of the geographic location of the mines, it can be seen that all of the top 10 South African mines are located in the Bushveld Complex. In particular, half of the top 10 mines are located in the Western region of the Bushveld Complex. Many of the other identified South African mines are also located in the Bushveld Complex (see Figure B.1 in Appendix B). This implies that palladium mining in South Africa, and therefore global palladium mining in general, has historically been vulnerable to events occurring in the Bushveld Complex, in particular the Western Limb area.

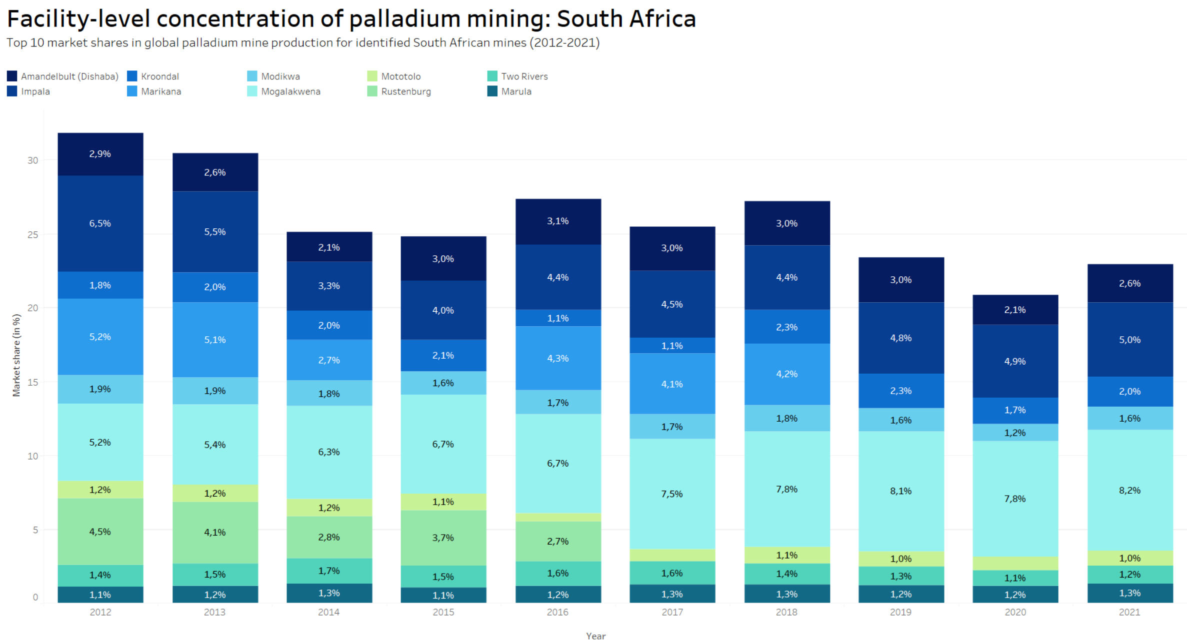

Figure 5.6: Market shares in global palladium mine production for identified South African mines during the years 2012-2021. For visual purposes only the top 10 mines in terms of market share are shown. Figure based on own calculations. Underlying facility-level production data retrieved from Buchholz et al. (2022), JOGMEC, and company publications. Underlying global production based on country-level production data from DERA (2020) and the USGS (Schulte, 2022, 2023).

5.3.3. Company level

The third sub-indicator that is considered to investigate the concentration of primary production is the primary production concentration on a company level. To investigate how the company-level primary production concentration has changed over time, the company-level HHI of primary palladium production is used as a proxy. To that end, the market shares in global palladium mine production[4] of the largest palladium mining companies are retrieved for the years 2010-2022 from Norilsk Nickel annual reports (2011-2023). Unfortuantely, Norilsk Nickel only reports the market shares of the largest companies. To account for the market shares of the remaining companies, lower and upper bounds for the HHI are computed again. Table 5.5 shows the computed lower and upper bounds of the company-level HHI as well as the corresponding level of concentration.

Based on the computed lower bounds, primary palladium production is moderately concentrated in 77% (10/13) of the years and highly concentrated in 33% (3/13) of the years. Based on the computed upper bounds, primary palladium production is also moderately concentrated in most of the years (54%) and highly concentrated in approximately 46% (6/13) of the years. Considering the level of concentration over time, no clear change in the company-level HHI over time is apparent from Table 5.5. Possibly, the company-level HHI did not change significantly during the years 2010-2022. Unfortunately, this cannot be directly established from Table 5.5 due to the unknown distribution of the market shares of the remaining companies not reported in the Norilsk Nickel annual reports. However, what can be established based on Table 5.5 is that, during the years 2010-2022, global palladium mining was moderately concentrated in most years and highly concentrated in at least 2010, 2014, and 2022.

To explore how the company-level concentration might have changed over time, the underlying market shares are considered in more detail. Figure 5.7 shows the company market shares in global palladium mine production for the largest palladium mining companies.

Based on Figure 5.7, it can be noted that the Russian company Norilsk Nickel is by far the largest palladium miner with a median market share of 41% during the years 2010-2022. The South African mining companies Anglo American Platinum (Angloplats) and Impala Platinum (Implats) are also significant palladium miners with median market shares of 21% and 13%, respectively. During the years 2010-2022, the combined market share of these three top producing companies ranged between 69%

[4]The market shares are based on refined metal output obtained from mined feedstock (Norilsk Nickel, 2021).

Mine	Location	Shareholders (%)
Amandelbult	Western Bushveld Complex	Anglo American Platinum Ltd. (100%)
Impala	Western Bushveld Complex	Impala Platinum Holdings Ltd. (96%), AME Employee Stock Ownership Plan (4%)
Kroondal	Western Bushveld Complex	Anglo American Platinum Ltd. (50%), Sibanye-Stillwater Ltd. (50%)
Marikana	Western Bushveld Complex	Sibanye-Stillwater Ltd. (95.25%), Incwala Resources Pty. Ltd.(4.75%)
Modikwa	Eastern Bushveld Complex	Anglo American Platinum Ltd. (50%), African Rainbow Minerals Ltd. (41.5%), Modikwa Communities (8.5%)
Mogalakwena	Northern Bushveld Complex	Anglo American Platinum Ltd. (100%)
Mototolo	Eastern Bushveld Complex	Anglo American Platinum Ltd. (100%)
Rustenburg	Western Bushveld Complex	Sibanye-Stillwater Ltd. (100%)
Two Rivers	Eastern Bushveld Complex	African Rainbow Minerals Ltd. (54%), Impala Platinum Holdings Ltd. (46%)
Union Section	Eastern Bushveld Complex	Impala Platinum Holdings Ltd. (73.26%), Black Economic Empowerment (26.74%)

Table 5.4: Location and shareholders for the year 2022 of the top 10 South African mines (in terms of market share). Location based on SFA Oxford (2023b, 2023c, 2023e). Shareholders data retrieved from JOGMEC (2023c).

Year	Lower bound: company-level HHI	Upper bound: company-level HHI	Level of concentration
2010	2602	2746	High
2011	2142	2542	Medium/High
2012	2424	2488	Medium
2013	2377	2458	Medium
2014	2538	2638	High
2015	2280	2380	Medium
2016	2411	2460	Medium
2017	2424	2460	Medium
2018	2257	2338	Medium
2019	2403	2524	Medium/High
2020	2422	2746	Medium/High
2021	2413	2462	Medium
2022	2614	2650	High

Table 5.5: Lower and upper bound of the company-level HHI for the years 2010-2022. Table based on own calculations. Underlying company market shares retrieved from annual reports by Norilsk Nickel (2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023a). Level of concentration based on thresholds by Silberglitt et al. (2013) and Van den Brink et al. (2022).

and 78% with a median value of 75%. This thus indicates that the top three palladium mining companies accounted for approximately three quarters of global palladium mine production in the last decade. Hence, these three companies seem primarily responsible for the moderate-to-high level of company-level concentration of global palladium mining.

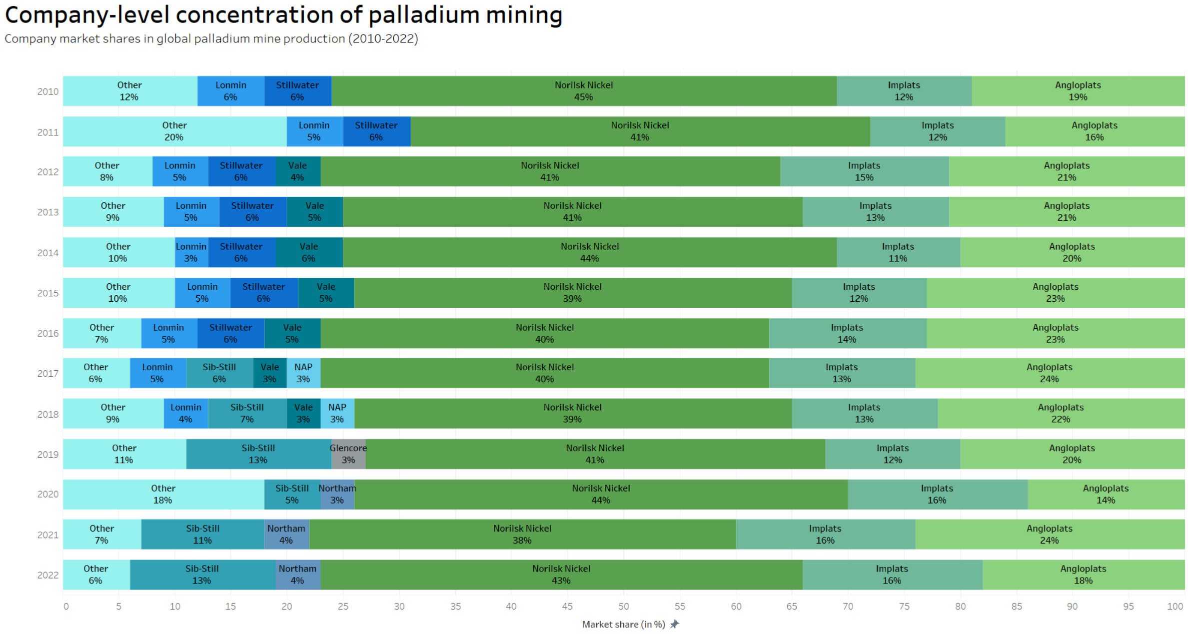

Figure 5.7: Company market shares in global palladium mine production during the years 2010-2022. Own figure based on data retrieved from Norilsk Nickel annual reports (2011-2023). Abbreviations: Sibanye-Stillwater (Sib-Still), North American Palladium (NAP), Impala Platinum Holdings Ltd. (Implats), Anglo American Platinum Ltd. (Angloplats), Northam Platinum Holdings Ltd. (Northam).

Furthermore, Figure 5.7 seems to suggest that global palladium mining might have become more concentrated on a company level over time due to company acquisitions. In particular, it can be noted that the market share of mining company Sibanye-Stillwater has increased over time. This can be explained by several acquisitions that the company has done in the last decade. In 2016, mining company Sibanye merged with Stillwater to form Sibanye-Stillwater (Reuters, 2016). Based on Figure 5.7, the impact of this acquisition on the company-level concentration of palladium mining seems to be limited, as the combined Sibanye-Stillwater market share in 2017 and 2018 does not differ significantly from Stillwater's market share in 2016. In 2019, Sibanye-Stillwater completed the acquisition of Lonmin, which was struggling financially after years of declining platinum prices (Heiberg and Shabalala, 2019). Sibanye-Stillwater's relatively high market shares in 2019, 2021, and 2022 (see Figure 5.7) seem to suggest that the Lonmin-acquisition did significantly raise Sibanye-Stillwater's market share and the overall company-level concentration of palladium mining. Indeed, other analysts concur that the Lonmin-acquisition strengthened Sibanye-Stillwater's market position in palladium mining considerably (Alexander et al., 2019). Around the same time, in 2019, Impala Platinum acquired North American Palladium (NAP) (Heiberg, 2019). Impala Platinum's relatively high market share in 2020-2022 (see Figure 5.7) seems to suggest that the NAP-acquisition further raised Impala Platinum's market share. As recently as May 2023, Impala Platinum further consolidated its market share in global palladium production by gaining a majority stake in the South African mining company Royal Bakofeng (Njini, 2023).

In addition to acquisitions of rival mining companies, palladium mining companies have also consolidated their market shares in global palladium mine production by acquiring individual palladium mines. For example, Sibanye acquired the Rustenburg mine (South Africa) in 2015 (Heiberg and Shabalala, 2019). In 2017, Northam Platinum acquired the Eland mine (South Africa) from Glencore (Kruger, 2017). Similarly, Anglo American Platinum acquired the Mototolo mine (South Africa) from Glencore in 2018 (Anglo American PLatinum, 2018).

Overall, it seems likely that global palladium mining has become more concentrated on a company level as a result of acquisitions in the period 2010-2022. This is problematic from a diversity of supply and resilience perspective, because it makes the palladium supply chain's ability to satisfy palladium demand (i.e. resilience) vulnerable to a small number of companies. In particular, the dominance of the Russian company Norilsk Nickel as the world's largest palladium miner is problematic from a Western geopolitical perspective. In this regard, it is interesting to note that two oligarchs with close ties to President Vladimir Putin, Oleg Deripaska and Vladimir Potanin, together hold a majority share in Norilsk Nickel (Davies, 2022; Rhoden-Paul, 2022; Statista, 2023).

5.4. Recycling

In contrast to the previous sections, this section focuses on secondary rather than primary palladium supply in the context of resilience. The third indicator is discussed, i.e. the contribution of recycling to meeting global palladium demand. In line with previous resilience studies (Mancheri et al., 2018; Sprecher et al., 2015) and as argued in Chapter 4, post-consumer recycling rather than pre-consumer recycling is analysed here. The end-of-life recycling input rate (EOL-RIR) is used as a sub-indicator, which is defined as the share of overall material demand that is satisfied through secondary supply (European Commission, 2023c). The share of global secondary palladium supply in global palladium demand is used as a proxy. Palladium supply and demand data are retrieved from Johnson Matthey (2023a). For the years prior to 1984, no secondary supply is reported by Johnson Matthey (2023a). Figure 5.8 shows the share of secondary supply in total supply as well as the EOL-RIR for the years 1984-2022. Figure 5.8 indicates that the contribution of secondary supply to total supply has signifi-

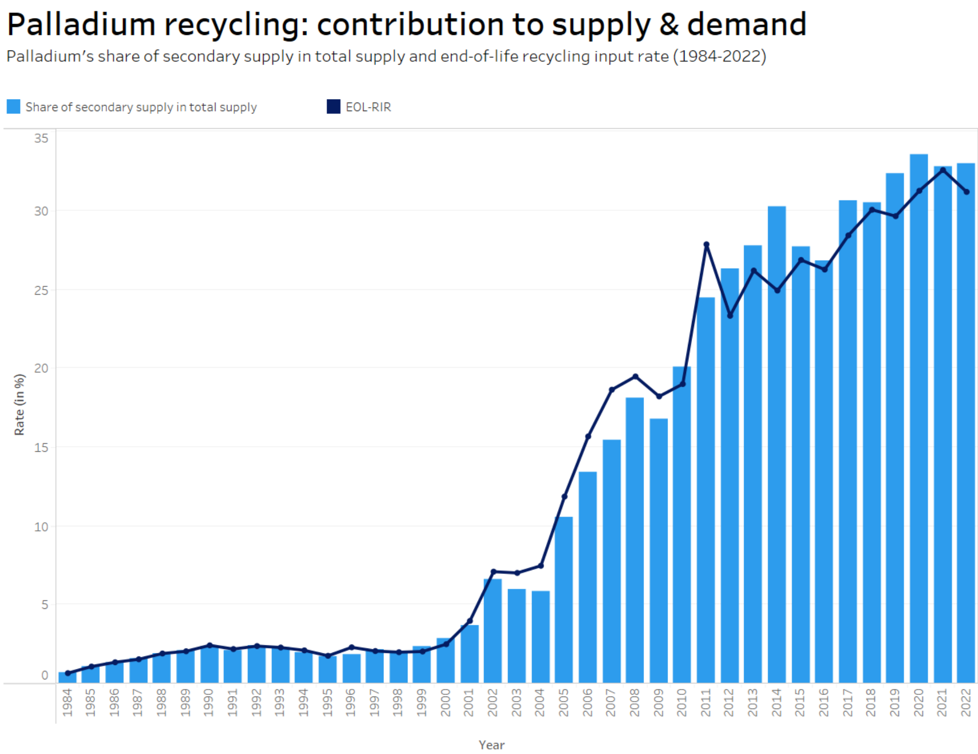

Figure 5.8: Palladium's share of secondary supply in total supply and the EOL-RIR for the years 1984-2022. Figure based on own calculations. Underlying supply and demand data retrieved from Johnson Matthey (2023a).

cantly increased over time. In 1984, the contribution to supply was negligibly small at approximately 0.7%. Particularly since 2005, however, the contribution of recycling to supply has increased dramatically to approximately 32.9% in 2022. Similar rates are reported by other authors. For example, Georgitzikis et al. (2023) reported that recycling's share in global palladium supply was more than 30% in 2021. Metals recycling company Umicore concurs that palladium recycling has been providing an increasingly sizeable proportion of overall palladium supply (2023). Clearly, recycling EOL products has become an increasingly important source of supply in addition to mining, indicating an increase in the diversity of overall supply over time. The increased contribution of recycling to palladium supply can be explained by the fact that, in relative terms, secondary supply increased much more than primary supply during the years 1984-2022. Total secondary supply increased by 15,395% from 20 koz in 1984 to 3099 koz in 2022, whereas total primary supply increased by approximately 113% from 2960 koz in 1984 to 6307 koz in 2022 (Johnson Matthey, 2023a). Still, the contribution of secondary supply to total supply (32.9%) is only slightly higher than the contribution of Russian primary supply (27.6%) or South African primary supply (24.2%).

A very similar trend can be observed for the EOL-RIR, which increased from approximately 0.7% in 1984 to approximately 31.2% in 2022. Similar EOL-RIRs around 30% were reported for the EU in recent years (European Commission, 2021, 2023b). The increased EOL-RIR indicates that the contribution of recycling to meeting palladium demand has increased significantly over time, thereby contributing to resilience.

5.4.1. Recycling by application

To further explore the drivers of the increase in palladium recycling over time, palladium recycling volumes by application are considered. Figure 5.9 shows the recycled palladium volumes by application for the years 1984-2022. Note that no electronics and jewellery recycling is identified by Johnson Matthey (2023a) for the years prior to 2005. Moreover, it can be noted that the overall increase in the amount of recycled palladium since 1984 is primarily attributable to an increase in recycling of EOL autocatalysts. Since 2005, palladium recycling of autocatalysts increased more than palladium recycling of electronics and jewellery, both in relative and absolute terms. In 2005, autocatalysts, electronics, and jewellery accounted for approximately 63.1%, 30.8%, and 6.1% of total secondary palladium supply. respectively. This changed to approximately 85.0%, 14.7%, and 0.3% in 2022. This change can be explained by the fact that both the volume of recycled palladium from electronic waste and the volume of recycled palladium from spent autocatalysts have increased significantly since 2005, but autocatalyst recycling has increased much more. More specifically, recycled palladium volumes from electronics increased by approximately 49.2% from 305 koz in 2005 to 455 koz in 2022. At the same time, recycled palladium volumes from autocatalysts increased by approximately 321.4% from 625 koz in 2005 to 2634 koz in 2022.

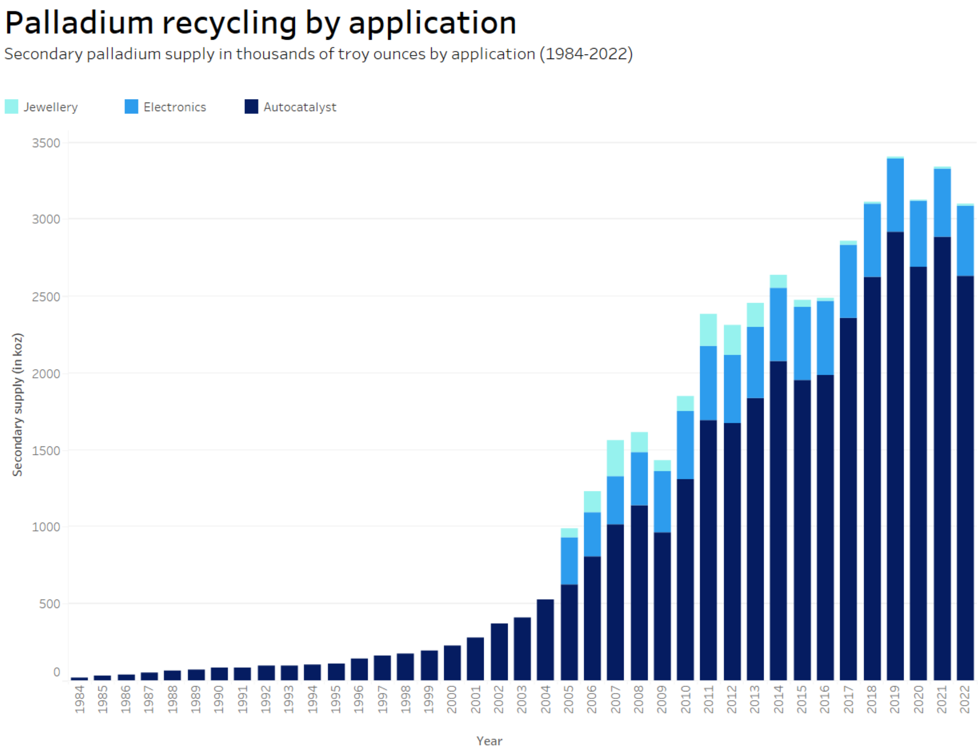

Figure 5.9: Secondary palladium supply in koz by application for the years 1984-2022. Own figure based on supply data retrieved from Johnson Matthey (2023a).

The significant increase in palladium recycling of autocatalysts over time can be explained by better autocatalyst collection and processing infrastructure as well as improved recycling efficiency over time, especially since the early 1990s (Wilburn and Bleiwas, 2005). In the 1970s, when PGM-bearing autocatalysts were introduced, there was no effective system of autocatalyst recycling and PGMs were typically not recovered from scrapped vehicles (Wilburn and Bleiwas, 2005). The most recent estimates identified indicate that palladium's recycling rate for autocatalysts is currently around 50-60% in developed countries (Xun et al., 2020). The recycling rate[5] is defined as the percentage of metal content in EOL products that remains after collection and processing and is an indicator of collection and processing efficiency (Graedel et al., 2018).

The fact that recycling of autocatalysts has historically contributed much more to secondary palladium supply than electronics recycling can primarily be explained by the fact that autocatalysts are by far the most common application of palladium. For reference, autocatalysts accounted for approximately 85% of global palladium demand in 2022[6]. Autocatalysts' large share in palladium-containing EOL products make recycling of autocatalysts in particular relatively profitable due to economies of scale.

In addition to scale differences, applications' different contributions to secondary supply can also partly be explained by differences in collection and processing efficiency. Whereas palladium's recycling rate for autocatalysts is around 50-55%, the recycling rate for electronics is only 5-10% (Graedel et al., 2018). Palladium's higher recycling rate for autocatalysts compared to electronics results from differences in collection and processing of EOL products. While there is a good collection infrastructure for EOL vehicles, the collection of EOL electronics is currently insufficient (Van de Camp, 2020; Wittmer et al., 2010). Globally, only around 17.4% of electronic waste was collected and recycled in 2019 (Tiseo, 2023). In terms of processing, recycling palladium from autocatalysts is easier and more economical than recycling from electronics. PGM recycling by disassembling autocatalysts from cars is relatively easy (Georgitzikis et al., 2023) and a single ICEV contains around 3 grams of palladium (Wilburn and Bleiwas, 2005). Modern electronics, however, typically contain only very small amounts of CRMs and/or in complex mixtures (alloys), making recycling uneconomical (Bastein and Rietveld, 2015). Illustratively, a metric tonne of EOL mobile phones is required to obtain only 18 grams of palladium (Gómez et al., 2023).

The improved autocatalyst collection and processing efficiency over time is also reflected by the increase in palladium's recycling rate for autocatalysts over time. Between 2000 and 2017, palladium's recycling rate for autocatalysts increased from 8%, 5%, 17%, and 38% in 2000 to 29%, 56%, 58%, and 54% for China, Europe, North America, and Japan respectively (Xun et al., 2020). This indicates that palladium's recycling rate increased significantly globally, but that regional disparities between developed and developing countries remain (Xun et al., 2020).

Overall, it can be concluded that both palladium's EOL-RIR and recycling rate significantly increased over time, especially this century. Palladium's recycling rate is now relatively high compared to other metals, indicating high recycling efficiency (European Commission, 2021; Georgitzikis et al., 2023). This can partly be explained by palladium's high value (Georgitzikis et al., 2023). What is striking, however, is that palladium's EOL-RIR remains significantly lower than its recycling rate. For the year 2021, the computed EOL-RIR is approximately 32.6% compared to an overall recycling rate of 47% (European Commission, 2021). This indicates that palladium's improved recycling over time has not been sufficient to keep up with growing demand (European Commission, 2021). This implies that recycling's contribution to resilience has historically increased, but has remains limited due to palladium's faster growing demand.

5.5. Concentration of trade flows

This section discusses the fourth indicator, i.e. the concentration of trade flows. As explained Chapter 4, trade flows of PGM ores and concentrates are not analysed in this section, because international trade statistics do not provide sufficient detail to separate trade flows of PGM ores and concentrates from trade flows of other precious metals (Georgitzikis et al., 2023; JRC, 2023b).

It is interesting to note, however, that PGMs are typically traded in the form of refined metals and that the trade of PGM ores and concentrates is very limited (European Commission, 2023c). This can be

[5]The recycling rate is also referred to as the EOL-RR in the literature.
[6]Own calculation based on demand data by Johnson Matthey (2023a).

explained by the fact that PGM mining and processing operations are typically integrated at or near the mine site (European Commission, 2023c; Gunn and Benham, 2009). Examples of this integration are Norilsk Nickel's Kola Division and Polar Division mining facilities in Russia (see Figures B.2 and B.3 in Appendix B). One explanation for this integration of mining and processing facilities is that transportation of PGMs in unrefined form is unpractical (and uneconomical). For reference, Norilsk Nickel (2023a) reports that a metric tonne of mined PGM ore and a metric tonne of PGM concentrate contain only approximately 7 and 86 grams of PGMs, respectively. In addition to this practical reason, there are also business strategic reasons for this vertical integration, such as synergy effects and exposure to higher value added products (Collins and Treacy, 2021). Illustratively, the Norilsk Nickel group does not only consist of mining and processing divisions, but also of transportation, energy, and commodity trading divisions (Norilsk Nickel, 2023a). The limited trade of PGM ores and concentrates is thus indicative of the vertical integration in the supply chains of PGMs. From a diversity of supply and resilience perspective, the vertical integration in the palladium supply chain is undesirable, because it makes the supply chain more dependent on individual companies. The vertical integration in the palladium supply chain is in line with a broader trend of vertical integration observed for CRMs in general (Collins and Treacy, 2021; Van de Camp, 2020).

Accordingly, this study focuses on trade flows of refined palladium only. Note that the traded refined palladium originates from a variety of sources, including mining, recycling, and stockpiles. The country-level concentration of refined palladium trade flows is considered as a sub-indicator. The country-level HHI of net exports of refined palladium is used as a proxy. To that end, the total value of net exports per country[7] of 'palladium, unwrought or in powder form' (HS711021) is retrieved from UN Comtrade (2023). In principle, UN Comtrade reports exports for the years 1988-2022. However, for most years, the data is considered severely incomplete. In particular, no exports are reported for Russia (Soviet Union) and/or South Africa in approximately 66% (23/35) of the years. This indicates a lack of historical data for Russian and South African exports of refined palladium. This is problematic when computing the level of concentration (HHI), because earlier sections indicated that these two countries are the largest producers of refined palladium derived from mining.

Hence, the HHI is only computed for years in which both Russian and South African exports are reported, i.e. the years 2006, 2007, and 2012-2021. Figure 5.10 shows the country-level HHI of net exports of refined palladium for these years.

Based on Figure 5.10, no clear increasing or decreasing trend over time can be observed. Rather, the HHI of refined palladium exports seems to have been relatively steady in recent years. This is in line with the findings of the previous sections. The previous section indicated that recycling's contribution to total palladium supply increased from approximately 26% in 2012 to 33% in 2021 (see Figure 5.8). This implies that changes in the concentration of total palladium supply remain primarily driven by changes in the concentration of primary supply. Accordingly, the relatively steady country-level concentration of exports during the years 2006-2007 and 2012-2021 is in accordance with the relatively steady country-level concentration of primary supply during these years (see Figure 5.1). This, in turn, can largely be explained by the relatively steady market shares of dominant miners Russia and South Africa during these years (see Figure 5.2).

What is striking is that the country-level HHI of refined palladium exports is less than half of the country-level HHI of palladium mining (see Figures 5.1 and 5.10). This indicates that, on a country level, palladium exports are much more diversified than palladium mine production. The difference can be explained by the fact that refined palladium not only originates from mining countries, but also from countries involved in recycling or stockpiling of palladium. Figure 5.11 below shows the market shares of the largest exporters of refined palladium in 2021. It can be noted that Russia and South Africa are not as dominant in palladium exports as they are in mining (see Figures 5.2 and 5.11). Russia's market share in 2021 is 40.2% and 23.6% for mine production and exports, respectively. South Africa's market share in 2021 is 39.4% and 14.7% for mine production and exports, respectively. The USA, on the other hand, has a much more significant market share in exports than in mine production: 16.4% versus 6.4%. This is due to the fact that the USA is both a significant palladium mining and recycling country. The UK, Italy, Belgium, Germany, and Switzerland are also major exporters of palladium, although they are not involved in palladium mining. This can be explained by the fact that the Johnson Matthey in the UK, Chimet in Italy, Umicore in Belgium, and Heraues in Germany are major recyclers of palladium (Chimet, 2023; Cowley and Ryan, 2023; Georgitzikis et al., 2023; Heraeus, 2023; Umicore,

[7] The considered partner country is 'the world' (i.e. partner code 0).

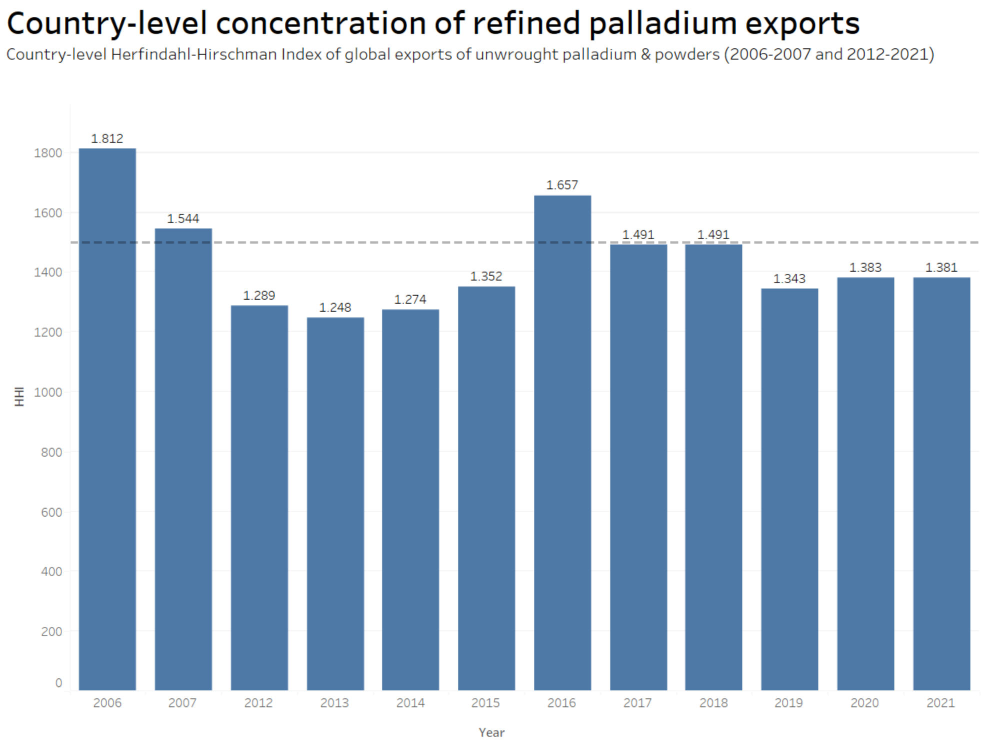

Figure 5.10: Country-level HHI of global exports of unwrought palladium and powders (HS711021) for the years 2006-2007 and 2012-2021. Note that the HHI ranges between 0-10,000 and that values above 1500 indicate a moderate level of concentration (Silberglitt et al., 2013; Van den Brink et al., 2022). Figure based on own calculations. Underlying export data retrieved from UN Comtrade (2023).

2023). An overview of PGM recycling facilities in the EU can be found in Figure B.4 in Appendix B. The UK and Switzerland are also major exporters of palladium, as they have traditionally been major trading hubs of palladium, allocating investor stockpiles from warehouses (vaults) in London or Zürich (Georgitzikis et al., 2023; LBMA, 2017).

Overall, it can be concluded that global palladium exports are quite diversified on a country level, especially compared to palladium mining. Recall that HHI values above 1500 and 2500 indicate moderately and highly concentrated markets, respectively (Silberglitt et al., 2013; Van den Brink et al., 2022). Hence, Figure 5.10 indicates that exports of refined palladium were moderately concentrated in 2006, 2007, and 2017 and unconcentrated in the remainder of the years covered. By contrast, recall that palladium mining was highly concentrated during all these years (see Figure 5.1). These findings suggest that palladium recycling and stockpiling have historically contributed to the diversification of supply. It can be hypothesised that the country-level HHI of palladium exports decreased during the first decade of this century due to the significant growth of recycling in these years. Unfortunately, the country coverage of UN Comtrade's export data is currently insufficient to verify this. The relatively diversified trade flows are desirable from a resilience perspective, because they enable users to switch to alternative suppliers in case of a national disruption (Van den Brink et al., 2022).

The findings in this section indicate that refined palladium exports are quite diversified on a global level, suggesting that in principle it is possible for a country to diversify its import sources. However, the supply base for individual countries can be more concentrated. For example, US imports of palladium were moderately to highly concentrated during the years 2018-2021 with Russia and South Africa accounting for 34% and 30% of imports, respectively (Schulte, 2023).

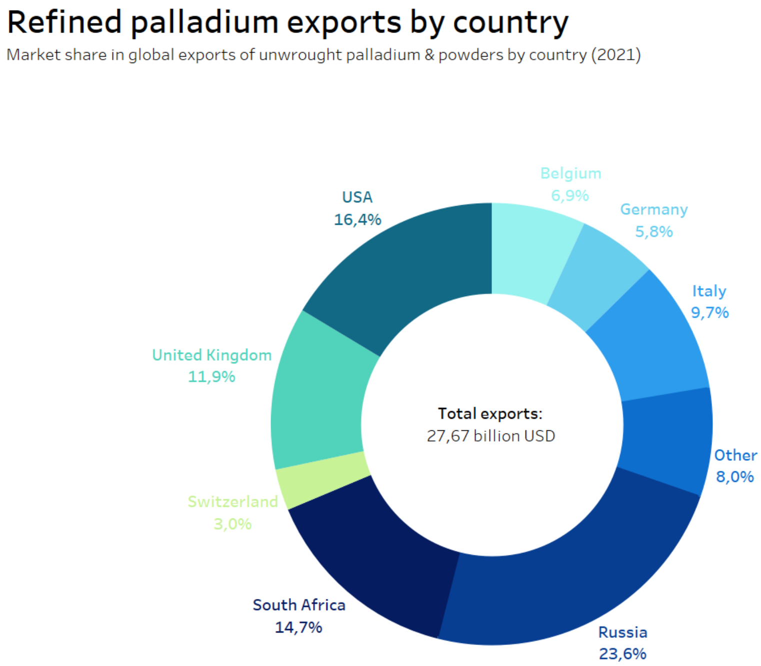

Figure 5.11: Market share in global exports of unwrought palladium and powders (HS711021) by country for the year 2021. Figure based on own calculations. Underlying export data retrieved from UN Comtrade (2023).

5.6. Chapter conclusion

This chapter investigated how the diversity of supply mechanism has changed over time and how this has affected resilience in the palladium supply chain. To that end, four indicators were considered: (i) the concentration of reserves, (ii) the concentration of primary production, (iii) recycling's contribution to meeting demand, and (iv) the concentration of trade flows.

In terms of the first indicator, this chapter showed that PGM reserves have been consistently highly concentrated during the years 1996-2023. PGM resources and reserves are highly concentrated in Russia, Canada, the US, Zimbabwe, and primarily South Africa (Hughes et al., 2021; Mudd, 2012; Mudd et al., 2018). South Africa and Russia together accounted for approximately 96-99% of global PGM reserves in the years 1996-2023. This indicates that future mine production is likely to remain highly concentrated in Russia and South Africa.

For the second indicator, the country, facility, and company levels were considered. On a country level, Russian dominance and the concentration of palladium mine production have significantly decreased over time. This is primarily attributable to the fact that South African mine production increased much more than Russian production during the years 1964-2022. Despite this decrease in concentration, palladium mine production has consistently been highly concentrated in Canada, the USA, Zimbabwe and especially Russia and South Africa during the years 1964-2022. This is problematic from a diversity of supply and resilience perspective, because it makes global palladium mine production vulnerable to supply disruptions in a handful of countries. On a facility level, palladium mine production overall was unconcentrated to moderately concentrated during the years 2012-2021. This indicates that the overall vulnerability to disruptions at individual mines is limited. However, global palladium production is particularly vulnerable to disruptions at the Kola Division and Polar Division mining facilities in Russia. These are the only mining facilities identified in Russia and have together consistently accounted for approximately 40% of global palladium mine production during the years 2012-2021. In South Africa, mine production is much more diversified on a facility level. The largest mining facility in terms of production is Mogalakwena, which accounted for approximately 8.2% of global mine production in 2021. In terms of geographic location, however, South African facilities are concentrated in the Bushveld Complex, especially the Western Limb area. This implies that South African production is particularly vulnerable to disruptive events in the Bushveld Complex. On a company level, palladium mine production was moderately to highly concentrated during the years 2010-2022. In particular, the dominance of the Russian company Norilsk Nickel as the world's largest palladium miner is problematic from a diversity of supply, resilience, and Western geopolitical perspective. The company owns the only two identified palladium mining facilities in Russia and accounted for around 40% of global mine production during the years 2010-2022. Moreover, this chapter indicated that global palladium mining has become more concentrated on a company level as a result of horizontal integration in the period 2010-2022. In particular, the market shares of Sibanye-Stillwater and Impala Platinum increased during these years as a result of the acquisitions of Lonmin and North American Palladium, respectively. This is problematic from a diversity of supply and resilience perspective, because it makes the palladium supply chain's ability to satisfy palladium demand (i.e. resilience) vulnerable to a small number of companies.

In terms of the third indicator, the EOL-RIR increased significantly from 0.7% in 1984 to 31.2% in 2022. The increases in the EOL-RIR, share of secondary supply in total supply, and recycling volumes were most significant this century and are primarily attributable to an increase in autocatalyst recycling. Autocatalyst collection and processing infrastructure were expanded over time, as recycling companies were incentivised by the relatively large amounts of palladium in EOL autocatalysts, easy disassembly of cars, and high palladium price (Georgitzikis et al., 2023; Wilburn and Bleiwas, 2005). By contrast, palladium recycling of EOL electronics has remained limited due to insufficient collection infrastructure as well as the relatively small amounts of palladium and complicated disassembly of EOL electronics. Furthermore, it was found that palladium's EOL-RIR remains significantly lower than its recycling rate, which indicates that palladium's improved recycling over time has not been sufficient to keep up with growing demand (European Commission, 2021). This implies that recycling's contribution to resilience has increased over time, but remains limited due to palladium's growing demand. With regards to the final indicator, it was found that the limited trade of PGM ores and concentrates is indicative of the vertical integration in the supply chains of PGMs. From a diversity of supply and resilience perspective, the vertical integration in the palladium supply chain is undesirable, because it makes the supply chain more dependent on individual companies. Moreover, it was found that exports of refined palladium were unconcentrated to moderately concentrated in the years 2006-2007 and 2012-2021. The UK, Italy, Belgium, Germany, and Switzerland were identified as major exporters of palladium, although they are not involved in palladium mining. This indicates that recycling and stockpiling practices make palladium trade flows much more diversified than palladium mine production, thereby contributing to diversity of supply and resilience.

6 The price mechanism

In this chapter, it is investigated how the price mechanism has changed over time and how this has affected the palladium supply chain's resilience. This chapter relates to the second sub-question: *How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?*

6.1. Introduction

In an efficient market, price acts as a communication tool that communicates how supply and demand are related. If material demand exceeds supply, one would expect prices to be high, which would then incentivise additional supply and disincentivise demand (and vice versa) (Bustamante et al., 2018). For material supply chains, this price dynamic is captured by the price mechanism. The price mechanism consists of multiple price feedback loops through which the price affects material supply and demand (Sprecher et al., 2015). Recall from Chapter 4 that this chapter's analysis of the price mechanism focuses on the first three main price feedback loops. These price feedback loops are visualised in Figure 6.1 in dark blue.

The first price feedback loop concerns the effect of the price of palladium's co-mined metals on the palladium's primary supply. Previous material supply chain resilience studies argued that increases in the prices of co-mined metals can incentivise investment in additional production capacity of these co-mined metals, thereby also raising primary supply of the material under consideration in the process, albeit after a time delay (Sprecher et al., 2015; Van den Brink et al., 2022). Indeed, palladium's primary supply is affected by the prices of the metals with which it is co-mined (Nassar et al., 2015; SFA Oxford, 2023d). Therefore, for palladium specifically, it can be hypothesised that the first price feedback effect has historically been positive and occurred only after a time delay.

The second price feedback loop concerns the effect of palladium's price on its primary supply. Previous studies argued that a material price increase can incentivise investment in additional production capacity, thereby raising primary supply after a time delay (Bustamante et al., 2018; Sprecher et al., 2015; Van den Brink et al., 2022). Hence, for palladium specifically, it can be hypothesised that the second price feedback effect has historically been positive and occurred only after a time delay.

The third price feedback loop concerns the effect of palladium's price on secondary supply. Previous material supply chain resilience studies argued that a material price increase can incentivise additional investment in recycling infrastructure (e.g. collection infrastructure or recycling production capacity), thereby raising secondary supply after a time delay (Sprecher et al., 2015; Van den Brink et al., 2022). Accordingly, for palladium specifically, it can be hypothesised that the third price feedback effect has historically been positive and occurred only after a time delay.

To investigate the temporal dynamics of the price mechanism and test the hypotheses formulated above, the price mechanism was operationalised in Chapter 4 based on three indicators: (i) companionality, (ii) the price elasticity of supply, and (ii) the cross price elasticity of supply.

Recall that the first indicator is the degree to which palladium is mined as a companion to other host metals (Nassar et al., 2015). As argued in Chapter 4, companionality is a relevant indicator to consider because it affects the first two price feedback loops. As a proxy for the first indicator, the

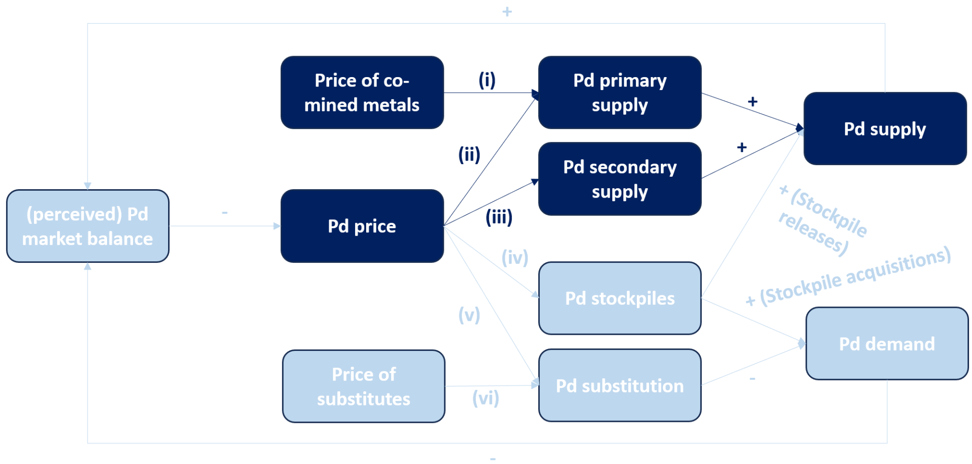

Figure 6.1: Conceptual model of the main price feedback loops in the palladium supply chain. Following System Dynamics convention, plus (+) and minus (-) signs between a factor A and factor B indicate that the factors move in the same direction or opposite direction, respectively (Bala et al., 2017). Pd refers to palladium. The six main price feedback loops are indicated by Roman numerals. The first three price feedback loops are highlighted in dark blue and are investigated in this chapter. Note that stockpiles can either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). Feedback loops based on Sprecher et al. (2015) and Van den Brink et al. (2022, see supplement).

share of primary palladium production in which palladium is mined as a companion is computed based on a selection of palladium mines globally.

Moreover, recall that the second indicator measures the responsiveness of the palladium supply to changes in the palladium price. The price elasticity of supply indicator can be used to quantify the direction and magnitude of the second and third price feedback loops. A price elasticity of supply above 1 indicates a relatively elastic supply (University of Minnesota, 2016). The regression-estimated price elasticity of supply is used as a proxy for the second indicator.

Recall that the third indicator measures the responsiveness of the palladium supply to changes in the price of another material. The cross price elasticity of supply indicator can be used to quantify the direction and magnitude of the first price feedback loop. The regression-estimated cross price elasticity of supply is used as a proxy for the third indicator.

An overview of this operationalisation of the price mechanism is provided in Table 6.1.

Indicator	Proxy	Data sources
Companionality	Share of primary palladium production where palladium is a companion	Buchholz et al. (2022)
		JOGMEC (2013-2023)
		Company publications
Price elasticity of supply	Regression-estimated price elasticity of supply	Johnson Matthey (2023a)
		Macrotrends (2023)
		World Bank (2023b)
Cross price elasticity of supply	Regression-estimated cross price elasticity of supply	Johnson Matthey (2023a)
		World Bank (2023b)

Table 6.1: Overview of the operationalisation of the price mechanism.

The remainder of this chapter consists of five sections. First, Section 6.2 investigates how palladium's companionality has evolved over time. Subsequently, Section 6.3 introduces the regression approach used to estimate the (cross) price elasticities of supply. Then, Section 6.4 discusses the results of the regression analyses of the (cross) price elasticities. Section 6.5 puts the findings from the companionality and regression analyses into context. Finally, Section 6.6 summarises this chapter's findings.

6.2. Companionality

In this section, the temporal dynamics of the first indicator of the price mechanism, i.e. companionality, are explored.

The literature suggests that palladium's companionality affects the first two price feedback loops in the palladium supply chain's price mechanism. A metal's primary supply not only depends on the metal's own price, but also on the price of the other metals with which it is mined together (Bustamante et al., 2018; Sprecher et al., 2017; Van den Brink et al., 2022). If a mine produces multiple metals, its production is usually determined by the price and demand dynamics of the metal that accounts for most of the economic revenue, i.e. the host metal (Kim and Heo, 2012; Van den Brink et al., 2022). The implication of this is that the supply of the other metals, i.e. the companions, is likely to be inelastic (Bastein and Rietveld, 2015; Bustamante et al., 2018; Sprecher et al., 2017; Van den Brink et al., 2022). All primary commercial sources of palladium are tied to mining of other metals due to palladium's low concentration in ores (DeCarlo and Goodman, 2022). Accordingly, palladium's primary supply depends not only on the palladium price, but also on the price of the metals with which it is co-mined (SFA Oxford, 2023d). The extent to which palladium's primary supply depends on the palladium price and prices of co-mined metals, respectively, depends on the degree to which palladium is mined as a companion to other host metals, i.e. companionality (Nassar et al., 2015).

To the best of the author's knowledge, the evolution of palladium's companionality over time has so far not been investigated. For the year 2008 specifically, Nassar et al. (2015) found a companionality for palladium of 97%. This indicates that palladium was almost exclusively mined as a companion to other host metals in 2008. The host metal differs per mine due to geological differences in the composition of deposits. In 2008, 53% of primary palladium production had nickel as host and 44% had platinum as host (Nassar et al., 2015). However, palladium's companionality has likely changed since 2008. After all, companionality is intrinsically dynamic, as metals' contributions to revenue can change over time (Nassar et al., 2015).

6.2.1. Approximating companionality: approach

Following the approach by Nassar et al. (2015), this study approximates palladium's companionality using mine-level production and revenue data. More specifically, palladium's companionality is measured by the share of primary palladium production in which palladium is mined as a companion (Nassar et al., 2015). To approximate this, a selection of palladium mines globally is identified. If a mine's revenue contribution by metal is highest for palladium, then its production is associated with palladium as a host. Conversely, if a mine's revenue contribution by metal is higher for another metal, then the mine's production is associated with palladium as a companion. Accordingly, annual revenue contributions by metal and palladium production volumes are retrieved for a selection of 15 palladium mines globally. These mines are located in Russia (2), South Africa (9), Zimbabwe (3), and Canada (1). The selected mines are owned by the three largest palladium mining companies: Norilsk Nickel, Anglo American Platinum, and Impala Platinum (recall Figure 5.7 in Chapter 5). To the best of the author's knowledge, Norilsk Nickel does not report the revenue contributions by metal of its individual mines. Hence, the revenue contributions by metal reported on a company level are used as an approximation for the revenue contributions by metal of Norilsk Nickel's Kola Division and Polar Division mines in Russia. These revenue contributions are retrieved from annual reports by Norilsk Nickel (2011-2022). For the remaining 13 mines, the revenue contributions by metal of the individual mines are retrieved from company publications (Anglo American Platinum Ltd., 2018, 2021, 2023; Impala Platinum Holdings Ltd., 2012, 2016, 2018, 2020, 2021). The mine-level palladium production volumes used to compute the companionality are the same as those used earlier for the facility-level concentration of primary production (see Chapter 5). Recall that these production volumes were retrieved from Buchholz et al. (2022), JOGMEC, and company publications (Norilsk Nickel, Anglo American Platinum, Impala Platinum, and Zimplats).

The time period 2010-2021 is selected to guarantee that the computed companionality reflects companionality on a global level[1]. For the selected time period 2010-2021, the selected mines' annual coverage of global primary palladium production ranges between approximately 51-71% with a median

[1]More specifically, the required data for Norilsk Nickel is only available for these years and is crucial to obtain good coverage of global primary production. Recall from Chapter 5 that Norilsk Nickel accounts for around 40% of global primary palladium production.

coverage of approximately 66% (see Table C.1 in Appendix C).

The results from the temporal analysis of palladium's companionality are discussed in the next subsection.

6.2.2. Approximating companionality: results

The temporal analysis of palladium's companionality suggests that palladium has primarily been mined as a companion metal up until 2016. Table 6.2 shows the results of computing palladium's companionality for the years 2010-2021 as well as palladium's price changes during these years. It can be noted that the companionality is 100% for the years 2010-2016. The actual companionality will be slightly lower than approximated, because there are mines with palladium as host that are not included in the companionality calculation due to a lack of data[2] Still, the calculated companionality provides a good approximation, covering the majority of global primary palladium production. The companionality of 100% is also close to the 97% found by (Nassar et al., 2015) for the year 2008. These findings suggest that palladium was almost exclusively mined as a companion metal during the years 2010-2016. This suggests that palladium's supply was likely primarily driven by the price and demand dynamics of the host metals with which it was mined. That is, palladium's primary supply was arguably relatively inelastic to changes in palladium price during the years 2010-2016. By contrast, Table 6.2 shows that the majority of palladium was mined as a host metal during the years 2017-2021. In 2020, only around 10% of palladium was still mined as a companion. This suggests that palladium's primary supply has become more responsive to changes in the palladium price since 2017.

Year	Companionality (%)	Palladium price change compared to previous year (%)
2010	100	67
2011	100	18
2012	100	-10
2013	100	16
2014	100	18
2015	100	23
2016	100	-4
2017	40	26
2018	25	3
2019	16	62
2020	10	77
2021	21	-23

Table 6.2: Palladium's companionality and price change compared to the previous year for the period 2010-2021. Companionality based on own calculations using revenue contributions by metal and palladium production volumes identified for 15 mines. The palladium price change compared to the previous year is based on own calculations using the real average annual palladium price (Macrotrends, 2023; World Bank, 2023b). Numbers are rounded to the nearest integer.

6.2.3. Palladium: from by-product to host

The previous subsection indicated that palladium's companionality exhibited a decreasing trend in recent years. To explore this decrease in palladium's companionality in more detail, a further distinction can be made between two types of companion metals: co-products and by-products. Co-products and by-products can be defined as companion metals that contribute at least 20% and less than 20% to a mine's revenue, respectively (Nassar et al., 2015). Figure 6.2 shows the annual percentage of palladium production mined as host, co-product, and by-product during the years 2010-2021.

It can be noted that palladium evolved from predominantly being a by-product in 2010-2013 to co-product in 2014-2016 to host metal in 2017-2021. This suggests that recent literature's view of palladium as a by-product (e.g., see DeCarlo and Goodman, 2022; SFA Oxford, 2023d) has in fact become outdated in recent years. Figure 6.2 indicates that palladium's revenue contribution relative to its co-mined metals has increased since 2010 and especially since 2017. Palladium's increased economic importance relative to its co-mined metals suggests that palladium's primary supply has become more

[2] For example, the East Boulder/Stillwater mine in the US is not included, where palladium accounted for most of the revenue in 2008 (Nassar et al., 2015).

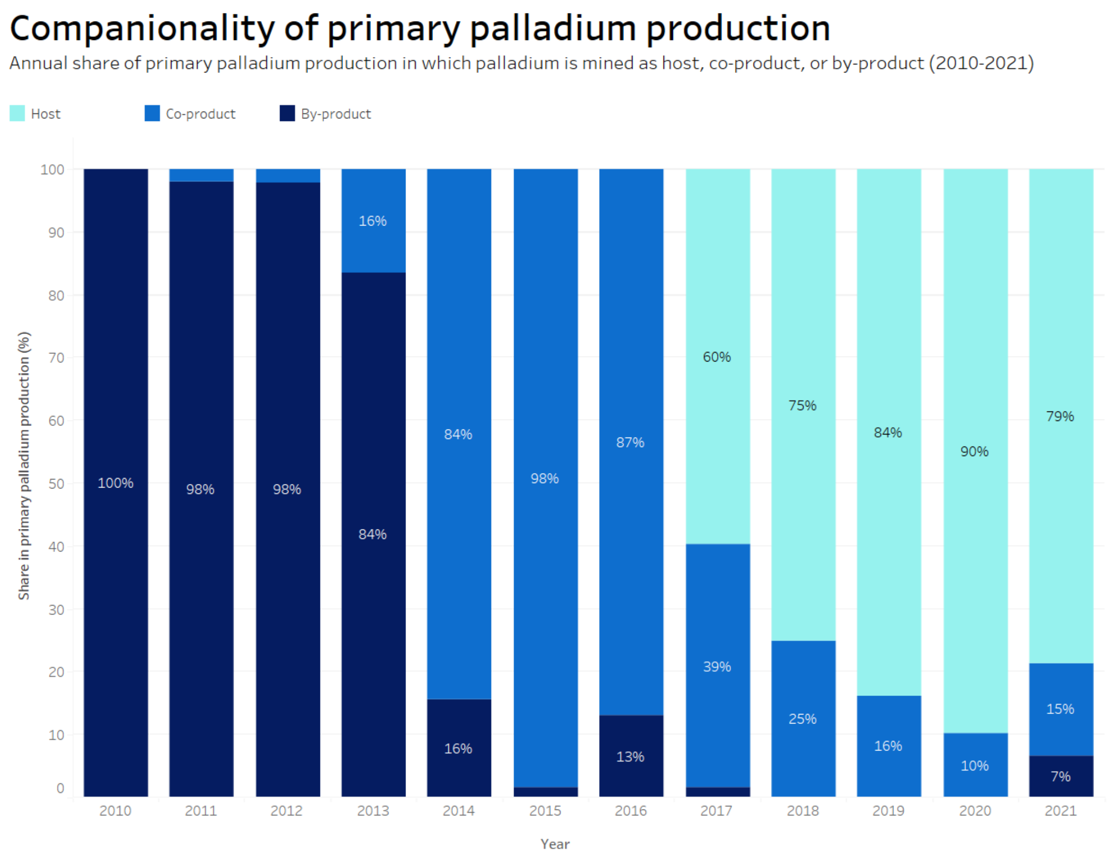

Figure 6.2: Annual share of primary palladium production in which palladium is mined as host, co-product, or by-product for the years 2010-2021. Own calculations based on revenue contributions by metal and palladium production volumes identified for 15 mines.

elastic to palladium price changes in recent years. A stronger responsiveness of palladium's primary supply to the palladium price could in turn imply that the resilience-promoting effect of the second price feedback loop has become stronger in recent years.

6.2.4. Palladium's host metals over time

The previous two subsections indicated that palladium was almost exclusively mined as a companion to other host metals during the years 2010-2016. These findings suggest that primary palladium supply was likely primarily driven by the price and demand dynamics of the host metals during these years. Therefore, it is interesting to identify palladium's host metals during the period 2010-2021.

Temporal analysis of palladium's host metals suggests that the host metals associated with palladium mining were nickel and platinum, palladium and platinum, and palladium and rhodium during the years 2010-2016, 2017-2019, and 2020-2021, respectively. Figure 6.3 shows primary palladium production by host metal for the period 2010-2021. It can be noted that, up until 2016, palladium was mined as a companion to host metals nickel and platinum. Considering the underlying data, nickel-based palladium production is primarily attributable to Russian mines and platinum-based palladium production is primarily attributable to South African and Zimbabwean mines. This can be explained by the fact that palladium is mainly found in nickel-dominant ores in Russia and PGM-dominant ores in South Africa and Zimbabwe (Encyclopaedia Britannica, 2023; Gunn and Benham, 2009). Since 2017, most palladium was mined as a host metal and the remainder was mined as a companion of the PGMs platinum and rhodium. This shift in palladium's host metals can be explained by the changing metal prices in these years. Between 2010 and 2021, the real prices of former hosts nickel (-8%) and platinum (-27%) decreased, whereas the prices of the new hosts palladium (+388%) and rhodium (+721%) increased significantly (see Table 6.2) (Macrotrends, 2023; World Bank, 2023b).

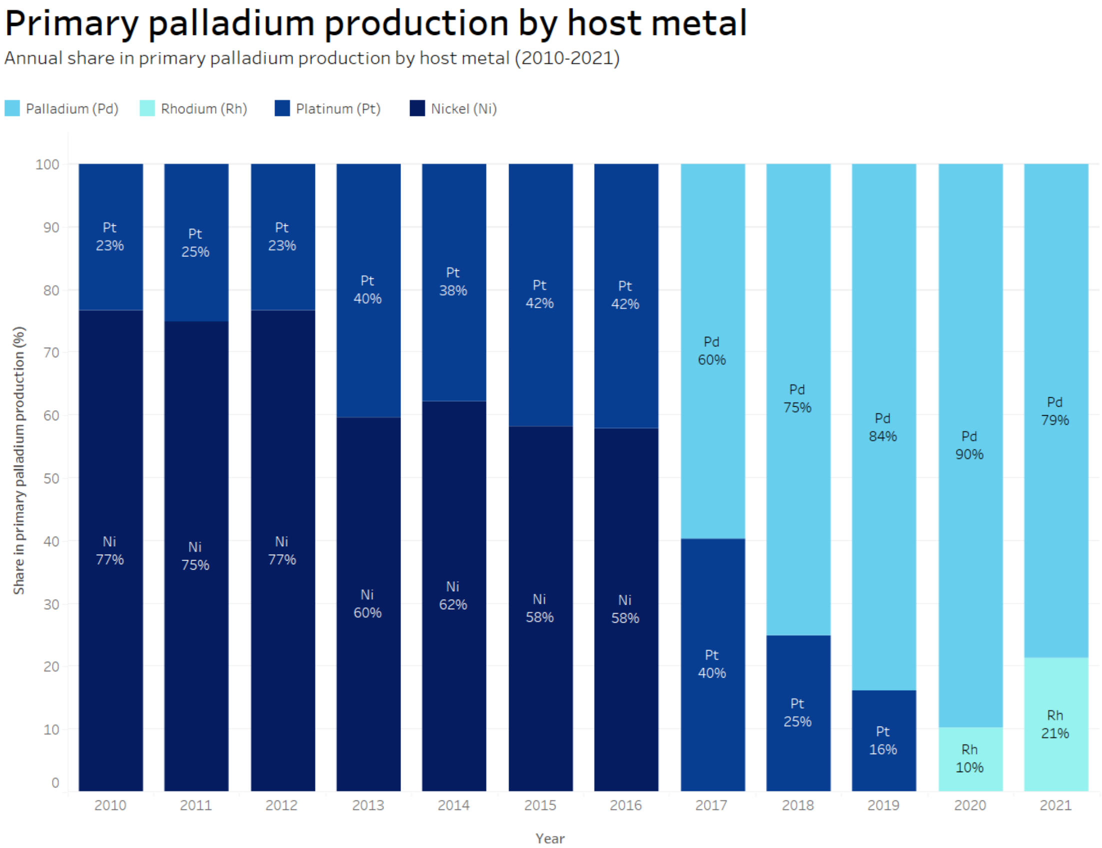

Figure 6.3: Annual share in primary palladium production by host metal during the years 2010-2021. Own calculations based on revenue contributions by metal and palladium production volumes identified for 15 mines.

Overall, it is found that palladium has historically primarily been mined as a companion metal to host metals nickel, platinum, and copper. The analysis above indicated that palladium was almost exclusively mined as a companion to nickel and platinum during the years 2010-2016. The literature suggests that palladium was primarily mined as a companion to nickel, platinum, and copper prior to these years (DeCarlo and Goodman, 2022; Nassar et al., 2015; SFA Oxford, 2023d). Moreover, the fact that platinum has historically typically been more expensive than palladium (see Figure **??** in Appendix E) suggests that platinum has historically had the largest revenue contribution of the two metals. That is, platinum rather than palladium has historically typically been the host in PGM-dominant ores.

In terms of the price mechanism, these findings suggest that the first price feedback loop has historically been stronger than the second price feedback loop. That is, palladium's primary supply has historically likely been more responsive to changes in the prices of hosts nickel, platinum, and copper than to changes in the price of palladium per se. It can thus be hypothesised that the cross price elasticities of palladium's primary supply with respect to nickel, platinum, and copper have historically been larger than the price elasticity of palladium's primary supply.

6.3. Regression approach: (cross) price elasticities of supply

To summarise, the previous sections introduced four hypotheses:

- The first price feedback effect has historically been positive and occurred only after a time delay.
- The second price feedback effect has historically been positive and occurred only after a time delay.
- The third price feedback effect has historically been positive and occurred only after a time delay.
- The first price feedback effect has historically been stronger than the second price feedback effect.

To test these hypotheses and investigate the temporal dynamics of the price mechanism, (cross) price elasticities of supply are estimated using regression modelling of historical time-series data. Price elasticities are commonly estimated by using a log-log linear regression model (Holmes et al., 2017). Accordingly, this study uses log-log linear regression models to estimate the (cross) price elasticities of palladium supply. More specifically, logged palladium supply is regressed on logged real palladium price and logged real price of platinum, nickel, and copper. The latter three metal prices are considered as explanatory variables, because palladium is often co-mined together with platinum, nickel, and copper (DeCarlo and Goodman, 2022; SFA Oxford, 2023d). To account for time lags, not only the prices in the same year as supply, but also the time-lagged prices are considered as explanatory variables. Time lags of 0-10 years are considered, because expanding primary supply can take up to 10 years (Van de Camp, 2020). Time lags of 0 up until 5 years are referred to as the short term and more than 5 years is referred to as the long term.

In addition to the four price variables, one additional explanatory variable is considered in the regression analyses to improve model accuracy: (logged) palladium supply in the previous year. The rationale behind this is that the inclusion of a lagged dependent variable in the model can help account for autocorrelation when using time-series data (Wilkins, 2018).

The regression analyses are conducted using the Statsmodels library (Seabold and Perktold, 2010) in Python. Annual palladium supply data is retrieved for the years 1980-2022 from Johnson Matthey (2023a). Nominal prices of palladium (Macrotrends, 2023), platinum, nickel, and copper (World Bank, 2023b) are retrieved and adjusted for inflation based on the Commodity Price Index (World Bank, 2023b).

Estimation of the (cross) price elasticities of supply is attempted for three palladium supply categories: primary supply, secondary supply, and overall supply (i.e. primary and secondary supply combined). The regression results are considered statistically significant and reliable if (i) the estimated coefficients are statistically significant at a 10% significance level (or better) and (ii) the assumptions of linear regression are not grossly violated. In particular, the following assumptions of linear regression are statistically tested: (i) the residual errors should be independent, (ii) the residual errors should be homoscedastic[3], and (iii) the residual errors should be normally distributed (Date, n.d.; Greene, 2012). In addition to these assumptions, it is also important to consider multicollinearity between the explanatory variables. Strong multicollinearity leads to inflated standard errors, which increases the possibility of Type II errors[4] (Greene, 2012).

The first assumption is considered satisfied if the Breusch-Godfrey test is passed at a 5% significance level. The null hypothesis of the Breusch-Godfrey test is that there is no autocorrelation of the residuals (Greene, 2012). The second assumption is considered satisfied if the Breusch-Pagan test is passed at a 5% significance level. The null hypothesis of this test is that the residuals are homoscedastic (Greene, 2012). The third assumption is considered satisfied if the Shapiro-Wilk test is passed at a 5% significance level. The null hypothesis of the Shapiro-Wilk test is that the residuals are normally distributed (Greene, 2012). To gain insight into the degree of multicollinearity between the explanatory variables, the condition number of the explanatory variables' correlation matrix can be computed (G. Chen, n.d.; Greene, 2012). A condition number above 1000 is commonly considered as indicative of strong multicollinearity and model instability (G. Chen, n.d.; Glass and Dozmorov, 2016).

Amongst the linear regression assumptions, the normality assumption is typically considered the least important (Gelman and Hill, 2006; Knief and Forstmeier, 2021). Regression results are typically robust to non-normality, even at small sample sizes (Gelman and Hill, 2006; Knief and Forstmeier, 2021).

6.4. Regression results: (cross) price elasticities of supply

In this section, the second and third indicators of the price mechanism are investigated. More specifically, the (cross) price elasticities are estimated for three palladium supply categories: primary supply, secondary supply, and overall supply. Following econometric convention (Imbens, 2021), the significance levels of the estimated (cross) price elasticities are denoted by one, two, or three asterisks for 10% (*), 5% (**), and 1% (***), respectively. For interpretation purposes, the explanatory variables are

[3]Homoscedasticity means that the variance of the residual errors is constant for all levels of the explanatory variables.

[4]An increased possibility of Type II errors (false negatives) means that there is an increased possibility of incorrectly finding no effect of the explanatory variable on the dependent variable, when actually there is an effect.

abbreviated in the reported regression results: logged time-lagged real palladium price (in 2022 US dollars/oz) (*ln(time-lagged Pd price)*), logged time-lagged real platinum price (in 2022 US dollars/oz) (*ln(time-lagged Pt price)*), to logged time-lagged real nickel price (in 2022 US dollars/metric tonne) (*ln(time-lagged Ni price)*), and logged time-lagged real copper price (in 2022 US dollars/metric tonne) (*ln(time-lagged Cu price)*).

6.4.1. Primary supply

The regression analyses of the (cross) price elasticities of primary supply suggest that there is no significant evidence for the first and second price feedback effects in the short term (0-5 years). It was attempted to estimate the (cross) price elasticities of primary palladium supply using a time lag for the price-related explanatory variables of 0-5 years. The findings suggest that primary palladium supply is primarily driven by non-price factors in the short term. For each time lag, none of the possible combinations of the five explanatory variables resulted in regression results that had significant coefficients for all explanatory variables and passed the Breusch-Godfrey and Breusch Pagan tests (for details, see Appendix C.2). That is, no reliable and statistically significant (cross) price elasticities were obtained using time lags of 0-5 years. This statistical insignificance indicates that, in the short term, the palladium, platinum, nickel, and copper prices have not significantly affected primary palladium supply. This suggests that the first and second price feedback loops have historically not significantly affected primary supply and, therefore, resilience, in the short term (0-5 years).

However, the regression analyses of the (cross) price elasticities of primary supply suggest that there is significant evidence for positive, but relatively inelastic, first and second price feedback effects in the long term (6-10 years). It was attempted to estimate the (cross) price elasticities of primary palladium supply using a time lag for the price-related explanatory variables of 6-10 years. Reliable and statistically significant price elasticities and cross price elasticities with respect to nickel were obtained for time lags of 6-10 years. Moreover, reliable and statistically significant cross price elasticities with respect to copper were obtained for time lags of 9-10 years. These regression results are summarised in Table 6.3 (for details, see Appendix C.2). It can be noted that the price elasticity of primary palladium supply for a time lag of 6 years is 0.246***. That is, a 1%-increase in the palladium price is associated with a 0.246%-increase in primary palladium supply 6 years later, on average, ceteris paribus. This indicates that primary palladium supply has historically positively responded to palladium price increases after a 6-year delay, but has been relatively inelastic. It can also be noted that the cross price elasticity of primary palladium supply with respect to nickel for a time lag of 6 years is 0.370***. That is, a 1%-increase in the nickel price is associated with a 0.370%-increase in primary palladium supply 6 years later, on average, ceteris paribus. This indicates that primary palladium supply has historically positively responded to nickel price increases after a 6-year delay, but has been relatively inelastic. Furthermore, it can be noted that the cross price elasticity of primary palladium supply with respect to copper for a time lag of 9 years is 0.341***. That is, a 1%-increase in the copper price is associated with a 0.341%-increase in primary palladium supply 9 years later, on average, ceteris paribus. These findings support the first two hypotheses formulated earlier: the first and second price feedback effects have historically been positive, but only after a time delay.

Moreover, the regression analyses of the (cross) price elasticities of primary supply suggest that the first price feedback effect has historically been stronger than the second price feedback effect. The regression results in Table 6.3 show that the cross price elasticities of primary palladium supply with respect to nickel and copper are larger than the price elasticities of primary palladium supply. This indicates that primary palladium supply has historically been more sensitive to changes in the nickel and copper prices than to changes in the palladium price. This finding supports the fourth hypothesis formulated earlier: the first price feedback effect has historically been stronger than the second price feedback effect.

To summarise, the findings above have four implications for resilience. Firstly, the first and second price feedback loops have historically contributed to resilience by raising primary supply. Secondly, the resilience-promoting (i.e. supply-raising) effect of the first and second price feedback loops has only occurred after a time delay of at least 6 years. This suggests that the first and second price feedback loops can arguably not significantly contribute to resilience during fast disruptions due to the time delay associated with expanding primary supply. Thirdly, the resilience-promoting (i.e. supply-raising) effect of the first and second price feedback loops has been relatively weak (inelastic). Finally, the first price feedback loop has historically contributed more to resilience than the second price feedback loop due

Time lag	6	9
Intercept	3.511*** (0.775)	4.856*** (0.649)
ln(time-lagged Pd price)	0.246***(0.057)	0.154*** (0.055)
ln(time-lagged Ni price)	0.370*** (0.082)	-
ln(time-lagged Cu price)	-	0.341*** (0.078)
Number of observations	37	34
R^2	0.627	0.560
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.052)	Yes (0.085)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.154)	Yes (0.789)
Normal residuals (p-value Shapiro-Wilk test)	Yes (0.667)	Yes (0.154)
Strong multicollinearity (condition number)	No (280)	No (231)

Table 6.3: Selected regression results for estimating the (cross) price elasticities of primary palladium supply for time lags of 0-10 years. Time lag refers to the time lag in years applied to the price-related explanatory variables. For the coefficient estimates, the number in parentheses indicates the standard error.

to its stronger positive effect on primary supply.

6.4.2. Secondary supply

The regression analyses of the price elasticities of secondary supply suggest that there is no significant evidence for the third price feedback effect within a period of 10 years. It was attempted to estimate the price elasticities of secondary palladium supply using a time lag for the palladium price of 0-10 years. For each time lag, none of the possible combinations of the two explanatory variables resulted in regression results that included the (time-lagged) palladium price, had significant coefficients for all explanatory variables, and passed the Breusch-Godfrey test (for details, see Appendix C.3). That is, the conducted regression analyses did not result in reliable and statistically significant price elasticities using time lags of 0-10 years. This statistical insignificance indicates that the palladium price has historically not significantly affected secondary palladium supply within a period of 10 years. This suggests that the third price feedback loop has historically not significantly affected secondary supply and, therefore, resilience within a period of 10 years.

There are two possible explanations for the finding above. One explanation could be that there is a significant effect of the (time-lagged) palladium price on secondary palladium supply, and therefore, resilience, but only after a time delay of more than 10 years. After all, time delays of more than 10 years were not considered in the regression analyses here. A second explanation could be that the palladium price per se is not a significant driver of secondary palladium supply. A possible reason for this may be that palladium only accounts for a small fraction of the economic value of palladium-containing EOL products. For example, palladium accounts for only 13% of the economic value of EOL mobile phones compared to 74% for gold (Gómez et al., 2023). Therefore, the prices of other materials may be more dominant drivers of the recycling of palladium-containing EOL products.

The statistical insignificance of the price elasticities of secondary palladium supply does not support the third hypothesis formulated earlier, i.e. the third price feedback effect has historically been positive and only occurred after a delay. That is, no statistical evidence is found for the argument by Sprecher et al. (2015) and Van den Brink et al. (2022) that a material price increase can raise secondary supply after a time delay through investment in recycling infrastructure.

6.4.3. Overall supply

The regression analyses of the (cross) price elasticities of overall supply suggest that there is no significant evidence that the price mechanism has affected palladium supply in the short term (0-5 years). It was attempted to estimate the (cross) price elasticities of overall palladium supply using a time lag for the price-related explanatory variables of 0-5 years. For each time lag, none of the possible combinations of the five explanatory variables resulted in regression results that had significant coefficients for all explanatory variables and passed the Breusch-Godfrey and Breusch Pagan tests (for details, see Appendix C.4). That is, the conducted regression analyses did not result in reliable and statistically significant (cross) price elasticities using time lags of 0-5 years. This statistical insignificance indicates that the palladium, platinum, nickel, and copper prices do not significantly affect overall palladium supply in the short term. This suggests that the price mechanism has historically not significantly affected supply and, therefore, resilience, in the short term (0-5 years).

However, the regression analyses of the (cross) price elasticities of overall supply suggest that there is significant evidence for a positive, but relatively inelastic, combined effect of the price feedback loops on supply in the long term (6-10 years). It was attempted to estimate the (cross) price elasticities of overall palladium supply using a time lag for the price-related explanatory variables of 6-10 years. Reliable and statistically significant price elasticities and cross price elasticities with respect to nickel were obtained for time lags of 6-10 years. Moreover, reliable and statistically significant cross price elasticities with respect to platinum and copper were obtained for time lags of 7-10 years. These regression results are summarised in Table 6.4 (for details, see Appendix C.4). It can be noted that the price elasticity of overall palladium supply for a time lag of 6 years is 0.362***. That is, a 1%-increase in the palladium price is associated with a 0.362% increase in overall palladium supply, on average, ceteris paribus. This indicates that overall palladium supply has historically positively responded to palladium price increases after a 6-year delay, but has been relatively inelastic. It can also be noted that the cross price elasticity of overall palladium supply with respect to nickel for a time lag of 6 years is 0.439***. That is, a 1%-increase in the nickel price is associated with a 0.439%-increase in overall palladium supply 6 years later, on average, ceteris paribus. This indicates that overall palladium supply has historically positively responded to nickel price increases after a 6-year delay, but has been relatively inelastic. Furthermore, it can be noted that the cross price elasticity of overall palladium supply with respect to platinum for a time lag of 7 years is 0.605***. That is, a 1%-increase in the platinum price is associated with a 0.605%-increase in overall palladium supply 7 years later, on average, ceteris paribus. This indicates that overall palladium supply has historically positively responded to platinum price increases after a 7-year delay, but has been relatively inelastic. Finally, Table **??** shows that the cross price elasticity of overall palladium supply with respect to copper for a time lag of 7 years is 0.458***. That is, a 1% increase in the copper price is associated with a 0.458%-increase in overall palladium supply 7 years later, on average, ceteris paribus. This indicates that overall palladium supply has historically positively responded to copper price increases after a 7-year delay, but has been relatively inelastic.

Moreover, it can be noted that overall palladium supply has historically responded more positively to price increases of host metals nickel, copper, and platinum than to price increases of palladium. Table **??** shows that the cross price elasticities of overall palladium supply with respect to nickel, platinum, and copper are larger than the price elasticities of overall palladium supply.

Time lag	**6**	**7**	**7**
Intercept	2.268** (0.855)	3.069*** (0.854)	2.991*** (0.717)
ln(time-lagged Pd price)	0.362*** (0.062)	0.236*** (0.078)	0.308*** (0.061)
ln(time-lagged Pt price)	-	0.605*** (0.147)	-
ln(time-lagged Ni price)	0.439*** (0.090)	-	-
ln(time-lagged Cu price)	-	-	0.458*** (0.089)
Number of observations	37	36	36
R^2	0.709	0.668	0.722
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.083)	Yes (0.075)	Yes (0.166)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.084)	Yes (0.214)	Yes (0.743)
Normal residuals (p-value Shapiro-Wilk test)	Yes (0.622)	No (0.021)	Yes (0.365)
Strong multicollinearity (condition number)	No (280)	No (225)	No (230)

Table 6.4: Selected regression results for estimating the (cross) price elasticities of overall palladium supply for time lags of 0-10 years. Time lag refers to the time lag in years applied to the price-related explanatory variables. For the coefficient estimates, the number in parentheses indicates the standard error.

Overall, the findings above are in line with the findings of the regression analyses of primary supply. The findings again support the first, second, and fourth hypotheses formulated earlier. Moreover, similar to the findings for primary supply, the findings above have four implications for resilience. Firstly, the price mechanism has historically contributed to resilience by raising overall palladium supply. Secondly, the resilience-promoting (i.e. supply-raising) effect of the price mechanism has only occurred after a time delay of at least 6 years. This suggests that the price mechanism can arguably not significantly contribute to resilience during fast disruptions due to the time delay associated with expanding supply. Thirdly, the resilience-promoting (i.e. supply-raising) effect of the price mechanism has historically been relatively weak (inelastic). Finally, the resilience-promoting effect of the price mechanism has historically been more sensitive to price changes of host metals nickel, platinum, and copper rather than to price changes of palladium.

6.5. Reasons for palladium's inelastic supply

The previous section found that, after a time delay of at least 6 years, primary and overall palladium supply have historically positively responded to palladium price increases, but have been very inelastic. This can also be noted when visualising the evolution of primary palladium supply and palladium price over time. Figure 6.4 shows that an increasing palladium price has coincided with a declining primary palladium supply in the last two decades.

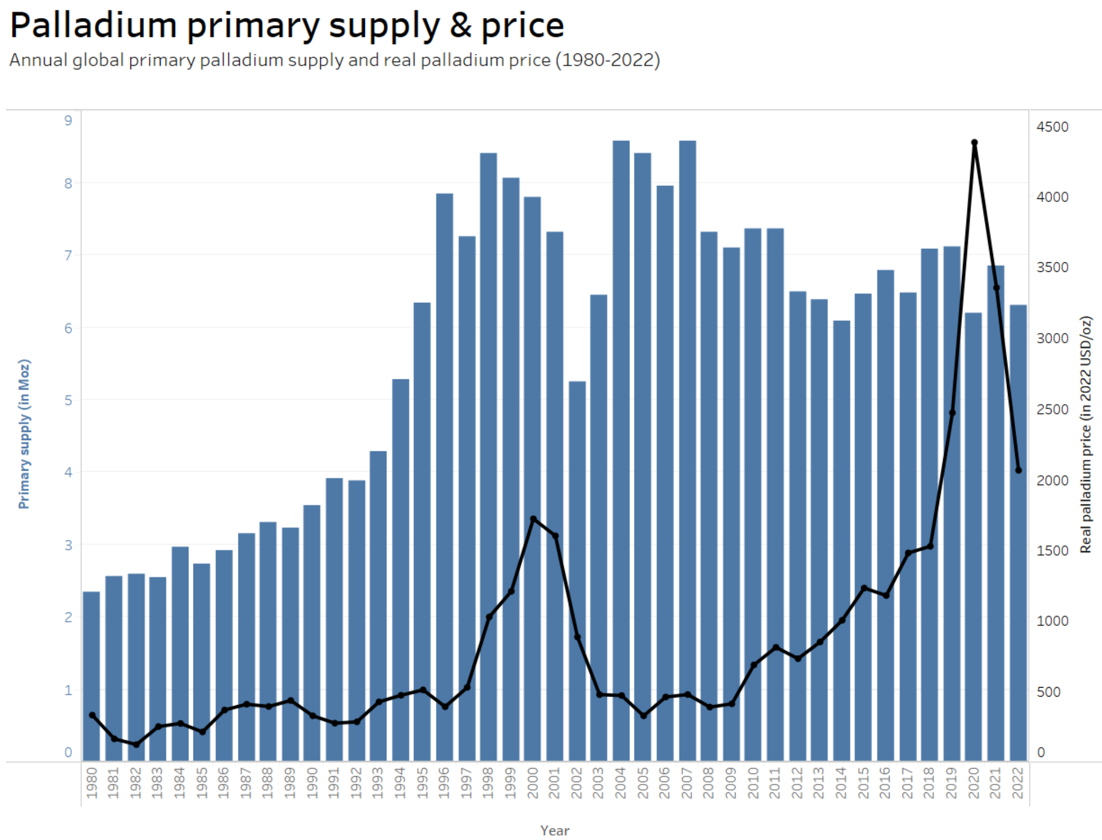

Figure 6.4: Global primary palladium supply (in millions of troy ounces) and average annual real palladium price (in constant 2022 US dollars per troy ounce) during the years 1980-2022. Global primary palladium supply is retrieved from Johnson Matthey (2023a). Palladium price is based on nominal prices from Macrotrends (2023) and corrected for inflation using the Commodity Price Index (World Bank, 2023b).

One explanation for the inelasticity of primary palladium supply is that primary palladium supply is has historically been more sensitive to the prices of palladium's host metals rather than to the palladium price. Indeed, the temporal analysis of companionality in the first section indicated that palladium was almost exclusively mined as a companion metal to host metals nickel and platinum during the years 2010-2016. Moreover, the estimated cross price elasticities indicated that primary and overall palladium supply have historically responded more positively to the prices of host metals nickel, platinum, and copper than to the palladium price.

Another explanation for the inelasticity of primary palladium supply is investors' reluctance to invest in capital intensive expansion of primary palladium production capacity due to the uncertain palladium price and demand outlook. In recent years, palladium has experienced extreme price volatility (DeCarlo and Goodman, 2022; Georgitzikis et al., 2023). Such price volatility can lead to uncertainty concerning future returns of mining investments, which can negatively affect investments in new supply (Bastein and Rietveld, 2015). Moreover, future palladium demand is expected to be negatively impacted by the electric vehicle EV transition, whereby palladium-containing ICEVs are replaced by BEVs that do not contain palladium-based autocatalysts (Hobson, 2023; SFA Oxford, 2019). This uncertain palladium demand outlook has made investors reluctant to invest in building new palladium mines in the last decade (Njini, 2022, 2023). Moreover, investors have been reluctant to invest in palladium resource exploration in the last decade (Casey, 2020). Illustratively, investment in South African PGM resource exploration almost halved from 72.3 million US dollars in 2013 to 36.5 million US dollars in 2022 (JRC, 2023a).

Overall, these findings suggest that the lack of investment in new primary palladium supply during a period of growing demand has been an important driver of the structural lack of resilience in the last decade. Illustratively, Figure 6.5 shows that a structural market deficit has coincided with an inelastic and slightly declining primary supply in the last decade. These findings confirm that long lead times for expanding mine production as well as the difficulty to justify large capital investments in case of unpredictable future demand are two factors that can contribute to CRM supply-demand imbalances (Gardner and Colwill, 2018).

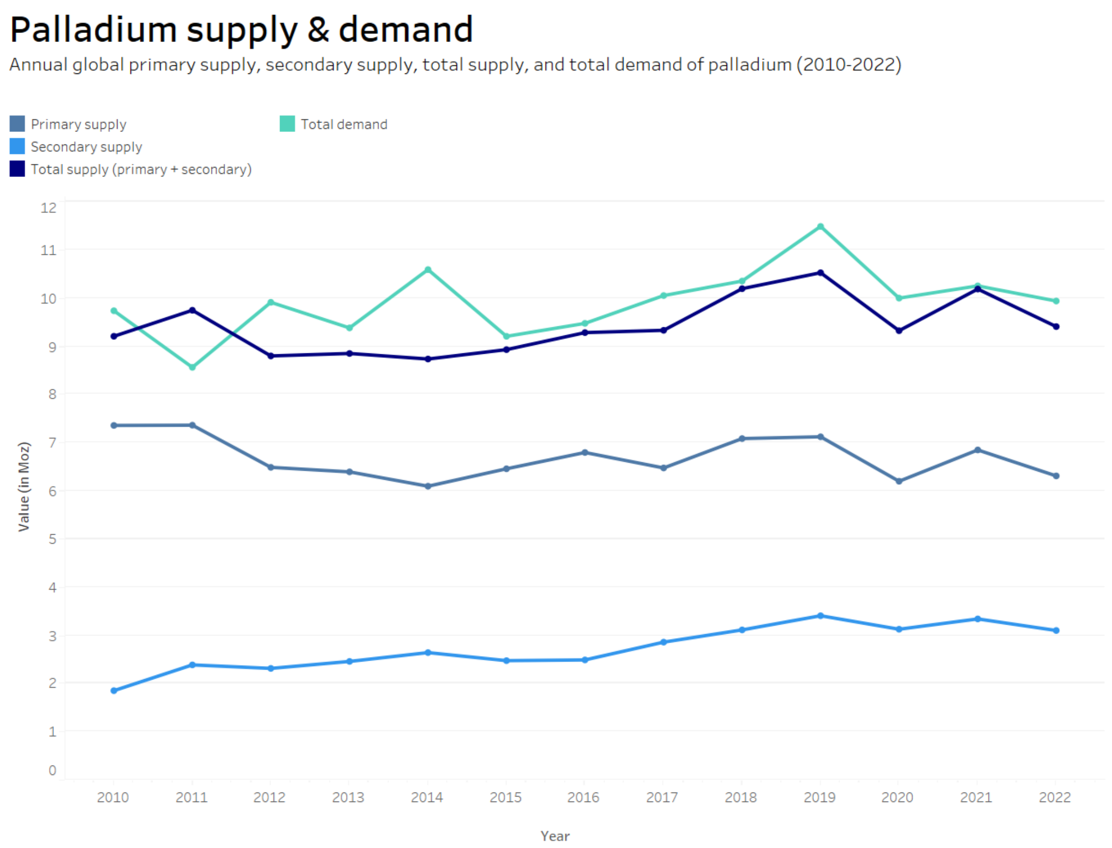

Figure 6.5: Global primary supply, secondary supply, total supply, and total demand of palladium (in millions of troy ounces) during the years 2010-2022. Own figure based on data retrieved from Johnson Matthey (2023a). Note that there has been a structural market deficit with total demand exceeding total supply since 2012.

6.6. Chapter conclusion

This chapter investigated how the price mechanism has changed over time and how this has affected resilience in the palladium supply chain. To that end, three indicators were considered: (i) companionality, (ii) the price elasticity of supply, and (iii) the cross price elasticities of supply with respect to three metals with which palladium is typically co-mined: platinum, nickel, and copper. For the (cross) price elasticities of supply, a distinction was made between primary supply, secondary supply, and overall supply.

It was found that palladium's companionality declined from approximately 100% in the years 2010-2016 to 10-40% in the years 2017-2021 due to palladium price increases. In contrast to the dominant view in the literature of palladium as a by-product, it was found that palladium evolved from by-product, to co-product, to host metal in recent years. This could imply that palladium's primary supply has become more responsive to the palladium price in recent years.

Moreover, it was found that the first price feedback loop has historically contributed to resilience by raising primary palladium supply, but only slightly and after a time delay of at least 6 years. Statistically significant, positive, and inelastic cross price elasticities of primary palladium supply were found using time lags for the price-related variables of 6-10 years. These findings indicate that price increases of palladium's host metals have historically slightly positively affected primary supply, but only after a time delay of at least 6 years.

Similarly, it was found that the second price feedback loop has historically contributed to resilience by raising primary palladium supply, but only slightly and after a time delay of at least 6 years. Statistically significant, positive, inelastic price elasticities of primary palladium supply were found using time lags for the price-related variables of 6-10 years. These findings indicate that palladium price increases have historically slightly positively affected primary palladium supply, but only after a time delay of at least 6 years. This limited resilience-promoting effect of the second price feedback loop, i.e. the inelasticity of primary palladium supply, can be explained by investors' reluctance to invest in new primary palladium supply due to the uncertain palladium price and demand outlook.

Furthermore, it was found that the third price feedback loop has historically not significantly affected resilience within a period of 10 years. No reliable and statistically significant price elasticities of secondary palladium supply were found using time lags for the palladium price of 0-10 years. This statistical insignificance indicates that the palladium price has not significantly affected secondary palladium supply within a period of 10 years.

Additionally, it was found that the first price feedback effect has historically been stronger than the second price feedback effect. The estimated cross price elasticities with respect to palladium's hosts (nickel, platinum, copper) were found to be larger than the price elasticities, both for primary and overall supply. This indicates that price increases of palladium's hosts have historically affected palladium's primary and overall supply more positively than palladium price increases. This can be explained by the finding that palladium has predominantly been mined as a companion to nickel, platinum, and copper up until 2016.

Finally, it was found that the price mechanism overall has historically contributed to resilience by raising overall palladium supply, but only slightly and after a time delay of at least 6 years. Statistically significant, positive, and inelastic (cross) price elasticities of overall palladium supply were found using time lags of 6-10 years for the price-related explanatory variables. The time delay of at least 6 years suggests that the price mechanism can arguably not significantly contribute to resilience during fast disruptions due to the time delay associated with expanding supply.

7 The stockpiling mechanism

In this chapter, it is investigated how the stockpiling mechanism has changed over time and how this has affected the palladium supply chain's resilience. This chapter relates to the second sub-question: *How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?*

7.1. Introduction

The stockpiling mechanism concerns the build-up of stockpiles of a material for future use. To investigate the temporal dynamics of the stockpiling mechanism, the stockpiling mechanism was operationalised in Chapter 4 based on two indicators: (i) the time palladium stockpiles can satisfy societal palladium demand when regular supply sources are disrupted and (ii) stockpile allocations. The first indicator reflects the ability of stockpiles to act as an additional source of supply when regular supply sources (i.e. primary and secondary supply) are disrupted. As a proxy, estimates of palladium stockpile size expressed in months of demand are used. The second indicator reflects whether the process of stockpile releasing and building has historically resulted in a mitigation or aggravation of market deficits. As a proxy, identifiable stockpile allocations are considered. An overview of this operationalisation of the stockpiling mechanism is provided in Table 7.1.

Indicator	Proxy	Data sources
Time stockpiles can satisfy demand when regular supply sources are disrupted	Estimated size of stockpiles expressed in months of demand	Bloomberg (2020)
		Reuters (2023)
		Johnson Matthey (2023a)
Stockpile allocations	Estimated identifiable stockpile allocations	USGS (2004, 2005, 1999b, 1994)
		Johnson Matthey (2023a)
		Reuters (2019, 2015)
		SFA Oxford (2016-2023)

Table 7.1: Overview of the operationalisation of the stockpiling mechanism.

The remainder of this chapter consists of six sections. This chapter distinguishes between three general types of actors who employ stockpiling: states, companies in the supply chain, and investors (Sprecher et al., 2015; Van de Camp, 2020). Accordingly, Sections 7.2, 7.8, and 7.9 investigate palladium stockpiling by states, companies, and investors, respectively. Subsequently, Section 7.10 discusses palladium stockpiling overall. Then, Section 7.11 addresses the interplay between the stockpiling and price mechanisms. Finally, Section 7.12 summarises this chapter's findings.

7.2. State stockpiling

This section investigates how state stockpiling of palladium has evolved over time and how this has affected resilience in the palladium supply chain. Two types of state stockpiles are distinguished: strategic and economic stockpiles (The White House, 2021). Strategic stockpiles are solely held to act as a buffer in case of emergency disruption events. Economic stockpiles are also used for economic purposes, for example to promote national industry or to profit from price volatility. The subsections below discuss state stockpiling by five major geopolitical actors: the EU, China, Japan, the United States, and Russia.

7.3. State stockpiling in the EU

In the EU, state stockpiling of palladium has historically been non-existent. At least as recently as 2021, the EU did not maintain any CRM stockpiles at the EU or individual member state level (Nakano, 2021; Rietveld et al., 2022). However, the outbreak of the COVID-19 pandemic contributed to a shift in thinking about the necessity of stockpiling to secure the supply of CRMs. In 2021, the European Parliament stated that it 'regret[ted] that the creation of strategic stockpiling is not yet part of the action plan and calls on the Commission to also focus on [⋯] strategic stockpiling' (European Parliament, 2021, p. C 224/29). In 2022, in the State of the Union Address, President of the European Commission Ursula von der Leyen identified strategic stockpiling as one of the main policy tools to mitigate supply risks (Rietveld et al., 2022; Von der Leyen, 2023). The possibilities for future EU strategic stockpiling will be further discussed in the Policy Implications chapter (Chapter 9).

7.4. State stockpiling in China

In China, economic state stockpiling of palladium remains unknown, but likely. China maintains a stockpile of CRMs through the National Food and Strategic Reserves Administration, usually referred to as the State Reserve Bureau (SRB) (Zhang and Daly, 2021). The Chinese state stockpile is an economic stockpile, actively used to intervene in metal markets to combat price volatility and support national industry (Home, 2020; The White House, 2021). The SRB is a secretive agency and the Chinese state stockpile is widely regarded as a 'black hole' (Davis, 2022; Van de Camp, 2020; Zhang and Daly, 2021). To the best of the author's knowledge, it is unknown whether the SRB also stockpiles palladium specifically. However, it is likely that the SRB stockpile also includes palladium, considering that China accounts for a significant share in global palladium demand and has only very limited potential for palladium mining within its own borders (de Wet, 2013; Mudd, 2012). Illustratively, Chinese palladium imports from Russia suddenly increased significantly (81.3% compared to the previous year) in the months following the Russian invasion of Ukraine, which some analysts believe could indicate palladium stockpiling (A. Chen, 2023; Davis, 2022).

7.5. State stockpiling in Japan

Japan has maintained a strategic state palladium stockpile since at least 2014 (IEA, 2022a; Nakano, 2021). Japan has maintained a stockpile of raw materials since 1983 through the Japan Oil, Gas, and Metals National Corporation (JOGMEC), which is part of the Ministry of Economy, Trade, and Industry (Nakano, 2021; Rietveld et al., 2022). The JOGMEC stockpile is strategic in nature, as its stocks are released in response to supply shocks (JOGMEC, n.d.). Over the years, particularly since the 2010 REE crisis with China, Japan has further expanded its stockpiling operations and added new materials to its stockpile (Rietveld et al., 2022). The specific ore types and quantities held by JOGMEC have not been disclosed for strategic purposes, but the stockpile targets are generally set at 60 days of domestic consumption (IEA, 2022a).

7.6. State stockpiling in the USA

The United States have held a strategic palladium stockpile since the Cold War era. In light of the disruption risks posed by World War II, the USA created a national raw materials stockpile in the Strategic and Critical Materials Act of 1939: the National Defense Stockpile (NDS) (IEA, 2022b; The White House, 2021). The stockpile is managed by the Defense Logistics Agency of the US Department of Defense (IEA, 2022b; The White House, 2021). The objective of the NDS is to maintain a stockpile of raw materials to mitigate supply chain shortages for defence and essential civilian industries in case of a national emergency event (IEA, 2022b; The White House, 2021). The NDS is explicitly not intended to be used for economic purposes, thereby making it a purely strategic rather than an economic stockpile (IEA, 2022b; The White House, 2021). The stockpile was at its height during the Cold War, with an estimated total value of 9.6 billion USD in 1989, but most of the stockpile was sold in the post-Cold War years (Clark, 2022).

To investigate how American state palladium stockpiling has evolved over time, data is retrieved for the two indicators of the stockpiling mechanism: (i) the time the stockpile can satisfy demand when regular supply sources are disrupted and (ii) identifiable stockpile allocations. The size of the palladium stockpile held by the NDS is reported for the years 1993-2005 by the USGS in its PGM Mineral Yearbooks (2004, 1999b, 2014b, 2015b, 2016, 1994, 2017, 2018). Based on the reported stockpile size, the annual stockpile allocations can be inferred. Table 7.2 shows the size of the NDS palladium stockpile in kilograms, the same amount expressed in months of global demand, and the corresponding allocations in thousands of troy ounces.

Year	Palladium held by the NDS at yearend (in kg)	Palladium held by the NDS at yearend (in months of global demand)	Impact of stockpile allocations on market balance (in koz)
1993	39300	3.5	0
1994	39300	3.0	0
1995	39300	2.4	0
1996	39300	2.4	0
1997	39300	2.0	0
1998	38800	1.7	16
1999	28200	1.1	340
2000	19000	0.8	295
2001	16300	0.9	86
2002	5870	0.4	335
2003	1170	0.1	151
2004	568	0.0	19
2005	0	0	18

Table 7.2: Size and allocations of the US palladium stockpile for the years 1993-2005. The size in kilograms is retrieved from the USGS (George, 2004, 2005; Hilliard, 1999b; Reese, 1994). The size expressed in months of demand (rounded to one decimal place) is based on own calculations using global demand data from Johnson Matthey (2023a). The impact of stockpile allocations on the market balance (in thousands of troy ounces) is inferred from the changes in the stockpile size. Note that a positive impact indicates a stockpile release that raises the palladium market balance.

The sale of the entire NDS palladium stockpile contributed to resilience during the years 1998-2005. Table 7.2 shows that the NDS palladium stockpile remained constant during the years 1993-1997, indicating that US state palladium stockpiling did not affect the palladium market balance, i.e. resilience, during those years. Moreover, the table indicates that the size of the NDS palladium stockpile decreased significantly during the years 1998-2005, both in terms of quantity and in terms of months of demand. The stockpile releases raised the palladium market balance during the years 1998-2005, thereby contributing to resilience. During the years 2006-2014, the NDS palladium stockpile was depleted (George, 2005; Loferski, 2014b) and therefore did not affect resilience.

In the period 2014-2018, small acquisitions of palladium stockpiles by the NDS had a negligible effect on resilience. During the period 2014-2018, while the palladium market experienced a structural market deficit (Johnson Matthey, 2023a), the NDS acquired less than 1 kilogram of palladium[1] in total (Loferski, 2015b; Loferski et al., 2016; Singerling, 2017; Singerling and Schulte, 2018). Comparing this negative allocation to the average global demand for 2014-2018 (Johnson Matthey, 2023a), this is equivalent to less than 0.0004% of global demand. Hence, the negative impact of this acquisition on resilience has been negligibly small during the years 2014-2018. The impact of US stockpiling on resilience in the years 2019-2022 is unknown due to a lack of data.

[1] In addition to 1 kilogram of palladium, the NDS also acquired alloyed material containing palladium, such as palladium-cobalt wire.

7.7. State stockpiling in Russia

Russia has held an economic palladium stockpile since the Cold War era. The Russian State Reserve, known as Gokhran, stockpiles various precious metals, including palladium (Cooper, 2011; Rapoza, 2012). Gokhran's palladium stockpiles were created for strategic purposes in the Soviet Union of the 1970s and 1980s (Kitco News, 2010; Risk and Policy Analysts Ltd., 2012), when Norilsk Nickel was still a state-owned company (Norilsk Nickel, 2023b). Gokhran is officially a strategic, but de facto a commercial stockpile: stock releases are used to generate additional government revenue and to support national industry (Risk and Policy Analysts Ltd., 2012). The economic nature of the state stockpile is also illustrated by the fact that Gokhran has historically been part of the Ministry of Finance (Gokhran of Russia, 2023). The exact size of the total Russian palladium stockpile as well as of stockpile allocations over time remain unknown, because they are considered Russian state secrets (George, 2005; Kitco News, 2010; United States Department of Defense, 2015).

To investigate how Russian state palladium stockpiling has evolved over time, data is retrieved for the two indicators of the stockpiling mechanism: (i) the time the stockpile can satisfy demand when regular supply sources are disrupted and (ii) identifiable stockpile allocations. Only a limited number of estimates for the overall size of the Russian palladium stockpile is identified. Estimates of Russian state stockpile allocations are retrieved from Johnson Matthey (2023a) and Alexander et al. (2019) for the years 2005-2013 and 2014-2019, respectively. No stockpile allocations are identified for the years 2014-2015 and 2018-2019. Figure 7.1 shows the estimated annual Russian state palladium stockpile sales in koz as well as the annual average real palladium price (in 2010 USD/oz) for the years 2005-2019.

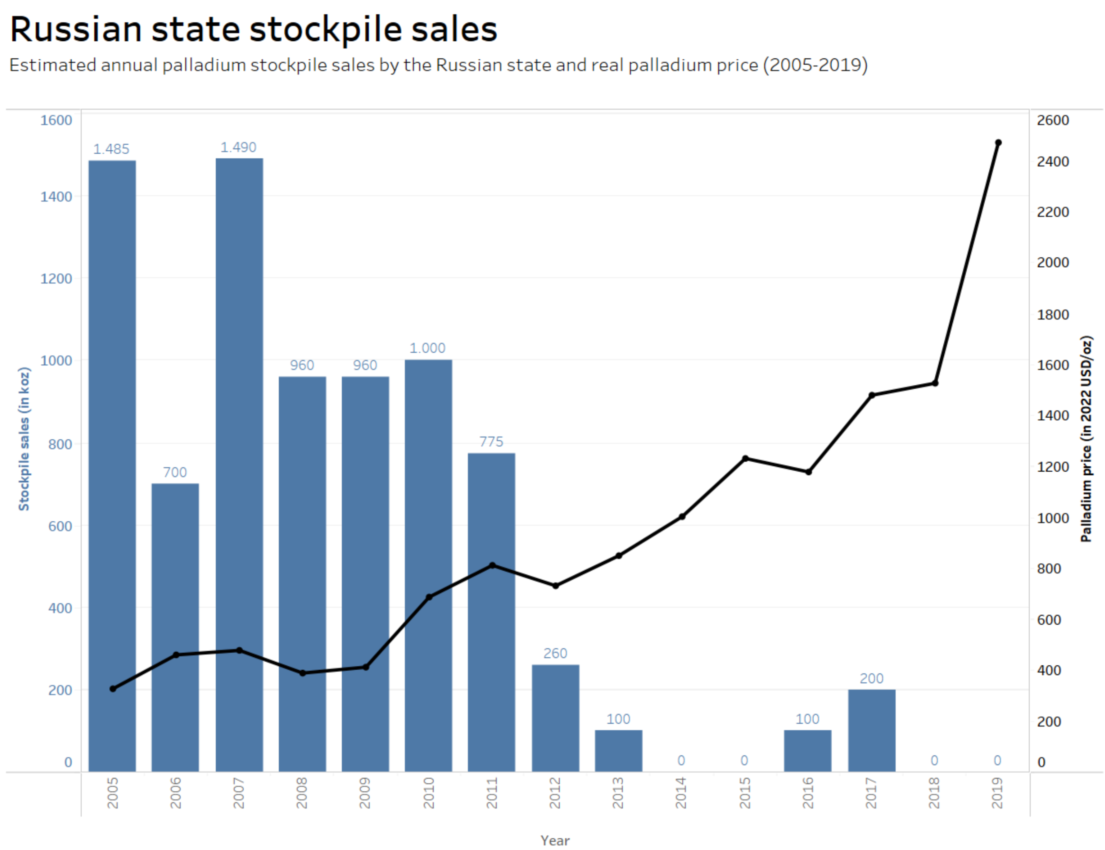

Figure 7.1: Estimated annual palladium stockpile sales in thousands of troy ounces by the Russian state (in blue) and annual average real palladium price in 2022 US dollars per troy ounce (in black) for the years 2005-2019. Stockpile sales are retrieved from Johnson Matthey (2023a) and Alexander et al. (2019) for the years 2005-2013 and 2014-2019, respectively. Real palladium price based on nominal palladium prices (Macrotrends, 2023) adjusted for inflation using the Commodity Price Index (World Bank, 2023b).

Significant palladium stockpile sales from Gokhran contributed to resilience in the 1990s and first decade of the 2000s. The Russian palladium stockpile is estimated to have amounted to 27-30 Moz at the beginning of the 1990s (Risk and Policy Analysts Ltd., 2012). Comparing this amount to estimated global demand in 1990 (Johnson Matthey, 2023a), this stockpile size is equivalent to as much as 93-103 months (8-9 years) of demand. After the collapse of the Soviet Union in 1991, a significant share of the stockpiles was sold in order to generate much-needed revenues for the new Russian Federation (Risk and Policy Analysts Ltd., 2012). Accordingly, the Russian palladium stockpile is estimated to have decreased to 10-12 Moz in 2003 (Risk and Policy Analysts Ltd., 2012). Comparing this amount to estimated global demand in 2003 (Johnson Matthey, 2023a), this stockpile size is equivalent to approximately 21-25 months of global demand. Hence, despite significant releases in the 1990s, the Russian state stockpile was still of considerable size at the beginning of this century. In the first decade of the 2000s, the significant palladium stockpile sales from Gokhran continued (see Figure 7.1). On average, the Russian stockpile sales accounted for approximately 13% of global palladium demand during the years 2005-2010[2]. As a result of these significant stockpile sales, the Russian palladium stockpile decreased considerably to approximately 3 Moz in 2012 (Risk and Policy Analysts Ltd., 2012). Comparing this to estimated global demand in 2012 (Johnson Matthey, 2023a), this is equivalent to approximately 4 months of global demand. The Russian palladium stockpile sales in the 1990s and first decade of the 2000s thus contributed to resilience by significantly raising the palladium market balance.

In the last decade, however, the Russian state palladium stockpile has likely not significantly contributed to resilience. Stockpile sales are only identified for the years 2012-2013 and 2016-2017 (see Figure 7.1). In 2016, the Russian state is estimated to have sold approximately 100 koz of palladium, including around 90 koz to the now-privatised Norilsk Nickel (Alexander et al., 2019; Fedorinova, 2016). Moreover, it can be noted that relatively small stockpile sales have coincided with an increasing palladium price and structural market deficit in the years 2012-2019 (see Figures 7.1 and 7.2). One would expect that the increasing palladium price and demand during the last decade would have incentivised more stockpile sales, not less. A likely explanation for the observed trend is therefore a reduction in the amount of palladium available for sale. Indeed, many palladium market analysts believe the Russian state palladium stockpile has been heavily depleted after years of significant sales (DeCarlo and Goodman, 2022; The Moscow Times, 2014). Accordingly, the head of Gokhran, Andrei Yurin, hinted Gokhran would actually start buying palladium from 2015 onwards (The Moscow Times, 2014).

The concurrent trends of relatively low Russian state palladium stockpile sales, structural market deficit, and increasing palladium price since 2012 suggest that Russian state palladium stockpiling may have had a negative long-term impact on resilience by suppressing palladium prices (see Figures 7.1 and 7.2). It can be noted that relatively high Russian stockpile sales coincided with market surpluses and a relatively low palladium price for most of the first decade of this century. Moreover, it can be noted that relatively low Russian stockpile sales coincided with a structural market deficit and an increasing palladium price since 2012. These findings suggest that the Russian state palladium stockpile sales may historically have been crucial to balance the palladium market. Simultaneously, these findings also suggest that Russian state palladium stockpile sales may have historically depressed palladium prices (Risk and Policy Analysts Ltd., 2012; The Moscow Times, 2014). The significant Russian state palladium stockpile sales have arguably kept the palladium price artificially low during the first decade of this century. The artificially low palladium price may in turn have inhibited expansion of palladium mining, processing, and recycling facilities, thereby contributing to the structural market deficit in the last decade. That is, the Russian state stockpile sales may have depressed regular (i.e. primary and secondary) supply in the long term. This hypothesis is supported by the findings in Chapter 6 of a lack of investment in new primary palladium supply and slightly declining primary palladium supply in the last decade.

Overall, the findings above suggest that Russian state palladium stockpile sales have positively affected resilience in the short term, but negatively affected resilience in the longer term. On the one hand, the Russian state palladium stockpile sales had a positive impact on resilience by raising the market balance in the short term (i.e. on an annual basis). On the other hand, the stockpile sales may have hindered the palladium supply chain in moving towards a state of increased mining and recycling. This finding thus illustrates the trade-off between short-term desirability for resilience and long-term

[2] Own calculation based on annual Russian stockpile sales and global palladium demand retrieved from Johnson Matthey (2023a).

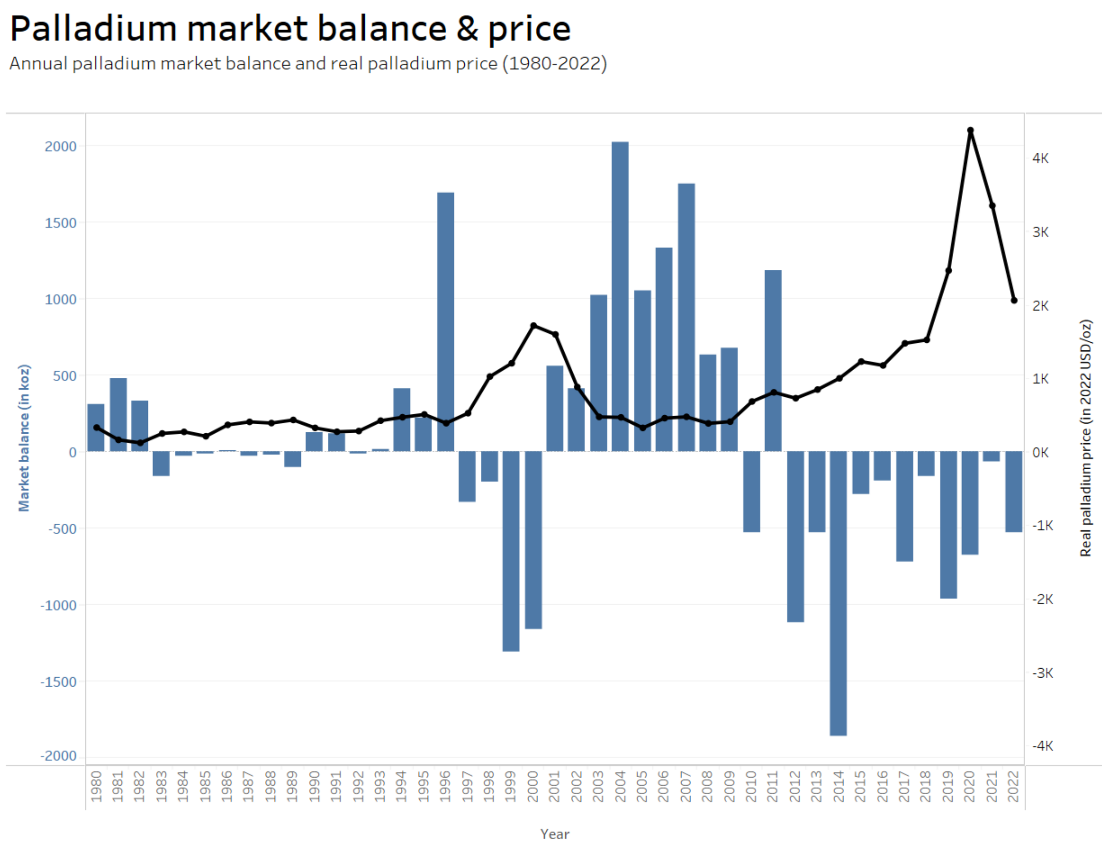

Figure 7.2: Annual palladium market balance (in koz) and average real palladium price (in 2022 USD/oz) for the years 1980-2022. Palladium market balance retrieved from Johnson Matthey (2023a). Real palladium price based on nominal palladium prices (Macrotrends, 2023) adjusted for inflation using the Commodity Price Index (World Bank, 2023b).

desire for system change (Sprecher et al., 2015).

7.8. Company stockpiling

Palladium stockpiles are held by companies along the palladium supply chain. This includes both producers (palladium mining companies) and users, such as car manufacturers (e.g. Ford, General Motors) and semiconductor manufacturers (Cowley and Ryan, 2023; Kilpatrick, 2022; Rapoza, 2012). These companies hold stockpiles in order to meet their (contractual) obligations to their customers further down the palladium supply chain. In some countries, such as Japan, the government also actively supports companies to maintain stockpiles on a voluntary basis (Rietveld et al., 2022). The chemical form of the palladium stockpiled by companies is unknown, but likely varies between PGM concentrates, refined palladium, and palladium-containing intermediate products depending on a company's place in the supply chain. The exact size of company palladium stockpiles is also unknown, as companies do not disclose such information for strategic purposes (Cowley and Ryan, 2023; Mazneva and Pakiam, 2020). Therefore, this study uses estimates of industry stockpile size and allocations from commodity research organisations and financial data providers.

To investigate how company palladium stockpiling has evolved over time, data is retrieved for the two indicators of the stockpiling mechanism: (i) the time the stockpile can satisfy demand when regular supply sources are disrupted and (ii) identifiable stockpile allocations. Estimates of total industry stockpiles are retrieved from Christian et al. (2023). Industry stockpile allocation estimates are retrieved from Reuters (Alexander et al., 2019; O'Connell et al., 2015) for the period 2005-2019. Industry stockpile allocations are only identified for the years 2011-2018 and shown in Table 7.3.

Identified estimates for industry palladium stockpiles' size and allocations suggest that company

Year	Impact of industry stockpile allocations on market balance (in koz)
2011	-50
2012	-100
2013	-500
2014	600
2015	-150
2016	140
2017	-290
2018	-160

Table 7.3: Impact of industry stockpile allocations on the market balance (in koz) during the years 2011-2018. Data retrieved from Reuters (Alexander et al., 2019; O'Connell et al., 2015). Note that a positive impact indicates a stockpile release that raises the palladium market balance by raising supply, whereas a negative impact indicates a stockpile acquisition that reduces the market balance by raising demand.

palladium stockpiling has mostly had a negative impact on resilience since 2011. Total industry palladium stockpiles are estimated to have increased from approximately 3 Moz in 2013 to 5 Moz in 2022 (Christian et al., 2023). Comparing these estimates to global palladium demand in the respective years (Johnson Matthey, 2023a), it is found that company palladium stockpiles increased from approximately 4 months of demand in 2013 to 6 months of demand in 2022. Accordingly, most stockpile allocations identified for the years 2011-2018 are stockpile acquisitions (see Table 7.3). These findings suggest that that companies have been net buyers of palladium stockpiles since 2011, thereby negatively affecting resilience by raising demand.

A specific historical example of speculative company palladium stockpiling negatively affecting resilience is the turn-of-the-century supply disruption. In the late 1990s and early 2000s a palladium price spike occurred when the Russian government hinted it was no longer going to sell any palladium from Gokhran (DeCarlo and Goodman, 2022; Rapoza, 2012). In response, major users of palladium in the downstream part of the supply chain, including the car companies General Motors and Ford, bought additional palladium in the open market, thereby raising demand and driving up prices (Rapoza, 2012). Accordingly, a palladium price spike and significant market deficit can be observed around the turn of the century (see Figure 7.2 in the previous section). The companies expected that the Russian decision would cause supply shortages and higher price levels in the future. Eventually, however, Russia did sell from its palladium stockpiles, causing prices to fall in the subsequent years (DeCarlo and Goodman, 2022; Rapoza, 2012). Consequently, downstream companies that had speculated higher palladium prices, such as Ford, incurred significant financial losses (Risk and Policy Analysts Ltd., 2012; White, 2002). This historical example illustrates that stockpiling can negatively affect resilience though a reinforcing feedback loop of higher prices and higher demand (Sprecher et al., 2015).

7.9. Investor stockpiling

A distinction can be made between two types of investor palladium stockpiles: palladium holdings by exchange-traded funds (ETFs) and non-ETF palladium investor stockpiles. Similar to stockpiling carried out by states and companies in the supply chain, most stockpiling employed by investors is opaque, with the exception of stockpiling by palladium exchange-traded funds (ETFs)[3]. Since 2007 investors can invest in these investment funds, which are typically backed by stockpiles of physical palladium bars, stored in vaults in London or Zurich, and (conveniently) managed by a custodian rather than by the ETF investors directly (LBMA, 2017; Renner et al., 2018). These palladium ETFs are listed on regular equity markets (LBMA, 2017; Renner et al., 2018). This makes stockpiling by ETFs relatively transparent, because equity-market regulations require ETFs to regularly report on their underlying holdings (e.g., see The U.S. Securities and Exchange Commission 2022). In fact, this makes palladium stockpiles held by ETFs the most visible type of palladium stockpile (Mazneva and Pakiam, 2020).

7.9.1. ETF investor stockpiles

Palladium stockpile acquisitions by ETFs negatively affected resilience during the years 2007-2014. Figure 7.3, which shows the size of palladium stockpiles held by several major palladium ETFs over

[3]Also referred to as exchange-traded products (ETPs).

time. It can be noted that the size of total palladium stockpiles held by ETFs increased significantly from the launch of the first palladium ETF in 2007 until around 2015. This can be explained by the initial popularity of these new physically-backed palladium ETFs amongst investors, which required the fund managers to raise the physical palladium stockpiles underlying these funds. Indeed, in these first few years, the overall palladium ETF market grew significantly and several new palladium ETFs were introduced (LBMA, 2017; The Economic Times, 2007). The initial popularity of these physically-backed palladium ETFs can partly be explained by the fact that they enabled investors outside the traditional palladium market to gain exposure to palladium. This included, for example, investors who were restricted to investing in equities and could previously only speculate on palladium via shares in mining companies (LBMA, 2017). As a result of the stockpile acquisitions during these years, the size of total ETF palladium stockpiles increased by approximately 42% from 2.189 Moz at the end of 2010 to 3.099 at the end of 2014 (see Table 7.4). Stockpiling by ETFs thus negatively affected resilience during the years 2007-2014 by raising palladium demand.

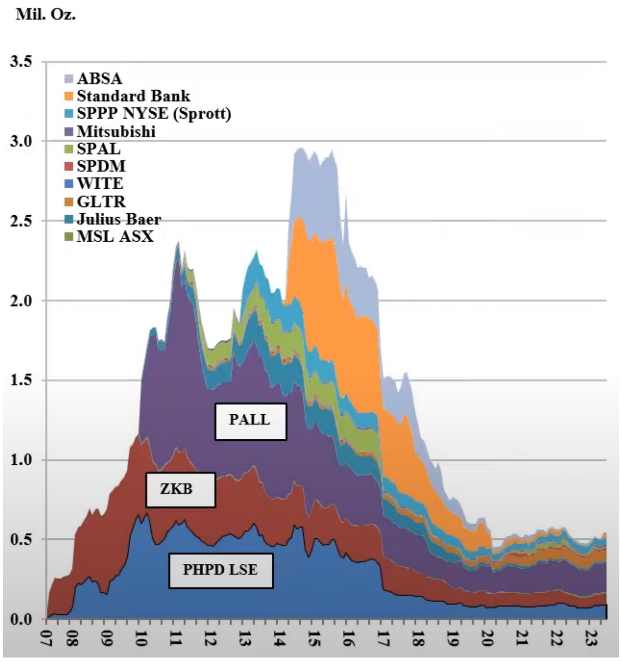

Figure 7.3: Palladium stockpile size (in millions of troy ounces) for several ETFs, based on monthly data through June 2023. Figure adopted from Christian et al. (2023, see time 1:08).

Year	Size of ETF palladium stockpiles at yearend (in Moz)	Size of ETF palladium stockpiles at yearend (in months of global demand)
2010	2.189	2.7
2011	1.684	2.4
2012	1.897	2.3
2013	2.184	2.8
2014	3.099	3.5
2015	2.373	3.1
2016	1.743	2.2
2017	1.272	1.5
2018	0.723	0.8
2019	0.617	0.6

Table 7.4: Estimated size of ETF palladium holdings at yearend for the years 2010-2019. The size in Moz is retrieved from Bloomberg (Mazneva and Pakiam, 2020). The size expressed in months of demand (rounded to one decimal place) is based on own calculations using global demand data from Johnson Matthey (2023a).

Conversely, palladium stockpile sales by ETFs, incentivised by the high palladium price, positively affected resilience during the years 2015-2019. Total palladium stockpiles held by ETFs have declined significantly between 2015 and 2019 (Hobson, 2020; Mazneva and Pakiam, 2020; SFA Oxford, 2019). Table 7.4 shows that total ETF palladium stockpiles decreased by as much as 74% from 2.373 Moz in 2015 to 0.617 Moz in 2019 (Mazneva and Pakiam, 2020). This decrease in ETF stockpiles since 2015 can be explained by the relatively high palladium price in these years in combination with investor expectations of a lower future palladium price (Harvey, 2017; Mazneva and Pakiam, 2020; SFA Oxford, 2019). These factors incentivised investors to sell palladium ETFs, which in turn required fund managers to reduce the underlying palladium stockpiles. Accordingly, Figure 7.4 shows a strong negative correlation between global palladium stockpile holdings by ETFs and the palladium price during the years 2016-2019. Stockpiling by ETFs thus positively affected resilience during the years 2015-2019 by providing an additional source of supply in a period of structural market deficit.

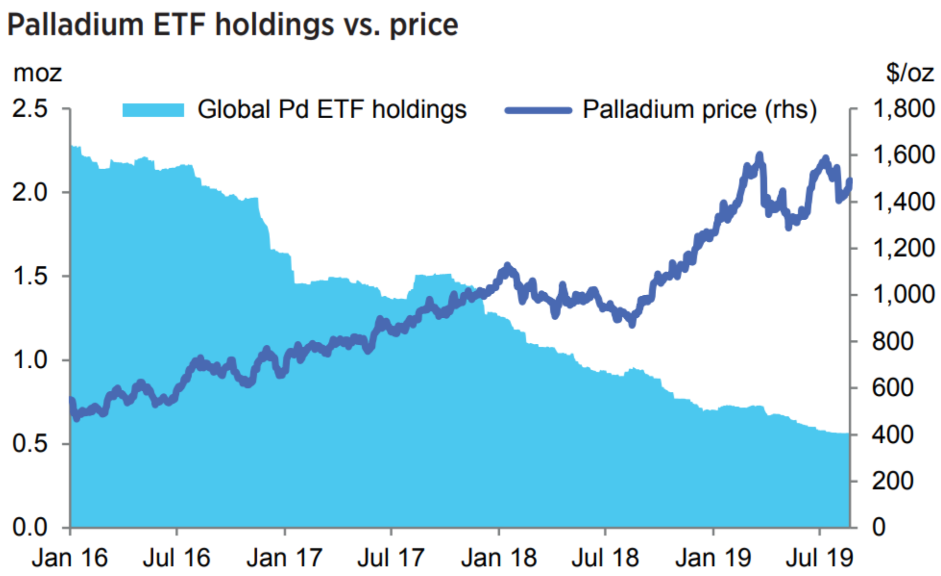

Figure 7.4: Global palladium stockpile size of ETFs (in millions of troy ounces) and the palladium price for the years 2016-2019. Figure adopted from SFA Oxford (2019, p. 8).

7.9.2. Non-ETF investor stockpiles

Non-ETF investors are a major stockpiling actor in the palladium market, but stockpile size and allocations are largely opaque. For reference, non-ETF investor palladium stockpiles are estimated at roughly 12 Moz for 2013 (Christian et al., 2023). Comparing this to estimated global demand in 2013 (Johnson Matthey, 2023a), this is equivalent to as much as 15 months of global demand. The palladium stockpile size estimates by CPM group (Christian et al., 2023) suggest that non-ETF investor stockpiles have historically been larger than ETF stockpiles, industry stockpiles, and Russia's state stockpile.

To investigate the impact of non-ETF investor stockpiling on the market balance over time, identifiable stockpile allocations by non-ETF investors are considered. To that end, total identifiable investor palladium stockpile allocations are retrieved from Johnson Matthey (2023a) for the years 2007-2022. These estimates cover all identifiable physical investment in palladium, including allocations by ETFs (Johnson Matthey, 2023b). Moreover, ETF investor palladium stockpile allocations are retrieved from SFA Oxford (2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023d) for the same time period. Identifiable non-ETF palladium stockpile allocations are inferred from the difference between these two data sets.

Palladium stockpile allocations by non-ETF investors seem to follow a similar trend as stockpile allocations by ETFs during the years 2007-2022. Figure 7.5 shows the estimated annual impact of identifiable non-ETF stockpile allocations on the palladium market balance as well as the real palladium price for the period 2007-2022. It can be noted that non-ETF investors have mostly negatively affected resilience during the years 2007-2015 through stockpile acquisitions. Moreover, it can be noted that non-ETF investors have mostly positively affected resilience during the years 2016-2022 through stockpile sales, incentivised by an increasing palladium price. These stockpile allocation trends for non-ETF investors are similar to the allocation trends observed for ETF investors.

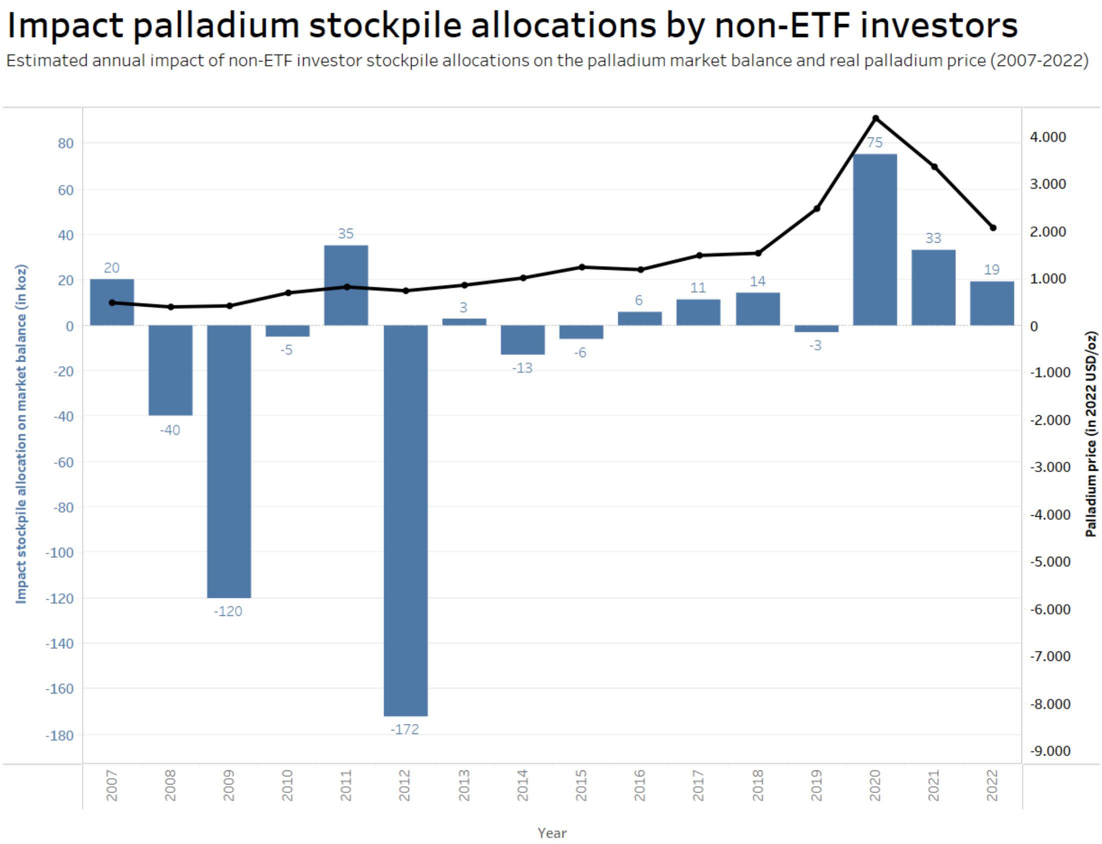

Figure 7.5: Estimated annual impact of identifiable non-ETF investor stockpile allocations on the market balance in thousands of troy ounces (in blue) and annual average real palladium price in 2022 US dollars per troy ounce (in black) for the years 2007-2022. Note that a positive impact indicates a stockpile sale that raises the market balance and a negative impact indicates a stockpile acquisition that reduces the market balance. Figure based on own calculations using data from Johnson Matthey (2023a) and SFA Oxford (2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023d). Real palladium price based on nominal palladium prices (Macrotrends, 2023) adjusted for inflation using the Commodity Price Index (World Bank, 2023b).

7.10. Stockpiling overall

Having discussed how stockpiling by states, companies, and investors have evolved over time, this section turns to stockpiling overall.

7.10.1. Size of total stockpiles

To investigate the time total stockpiles can satisfy demand when regular supply sources are disrupted, the estimated size of total stockpiles relative to demand is considered as a proxy. Commodity research organisation Metals Focus has estimated total palladium stockpiles for the years 2010-2022 (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020; Patel and Shivaprasad, 2023). In addition, global palladium demand estimates for these years are retrieved from Johnson Matthey (2023a). Figure 7.6 shows the estimated size of total palladium stockpiles in Moz and the same amount expressed in months of global demand for the years 2010-2022.

It can be noted that total palladium stockpiles significantly declined during the years 2010-2022. More specifically, total palladium stockpiles are estimated to have decreased by approximately 30.5% from 17.7 Moz in 2010 to 12.3 Moz in 2022 (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020). Moreover, it can be noted that the total palladium stockpile size in Moz is estimated to have slightly increased in 2011 and 2021, but consistently decreased during the remainder of the years. The composition of the total palladium stockpile and the underlying stockpile allocations causing the total stockpile's decline remain largely unknown due to the opacity in stockpile reporting.

The stockpile allocations identified in the previous sections suggest that the overall decline in total palladium stockpiles during the years 2010-2022 is primarily attributable to stockpile releases by the Russian state and ETFs. To gain some insight into the contribution of different stockpiling actors to changes in total palladium stockpiles, the estimated change in total stockpile size is compared to the previously identified stockpile allocations. The net allocation of total stockpiles during the years 2010-2022 amounts to an outflow of approximately 5355 koz[4]. For this same period, a total net outflow of 2435 koz was identified for the Russian state stockpile (see Figure **??**). Moreover, a total net outflow of 705 koz for ETF stockpiles and a total net inflow of 3 koz for non-ETF investor stockpiles were identified (see previous section). Finally, a total net inflow of 510 koz for industry stockpiles was identified (see Table 7.3). Although only identifiable stockpile allocations are considered, these findings suggest that the stockpile allocations by the Russian state and ETFs accounted for the majority of the decline in total stockpiles during the years 2010-2022.

In line with the decline in the size of total stockpiles, the time stockpiles can satisfy demand when supply is disrupted significantly decreased during the years 2010-2022. Figure 7.6 shows total palladium stockpiles are estimated to have decreased by approximately 31.7% from 21.8 months in 2010 to 14.9 months in 2022. It can be noted that the time stockpiles can satisfy demand fluctuated between 2010 and 2015. During the years 2010-2015, the time stockpiles can satisfy demand did not continuously decrease despite a continuous decline in total stockpile size due to demand fluctuations. Furthermore, it can be noted that the time stockpiles can satisfy demand did consistently decrease during the years 2016-2019. This can be explained by the fact that a continuous decline in total stockpiles coincided with a continuous increase in demand during these years. During the years 2020-2022, the time stockpiles can satisfy demand was relatively steady due to fluctuations in the total stockpile size and slightly declining demand.

Overall, the decline in both the total stockpile size and the time stockpiles can satisfy demand during the years 2010-2022 suggests that the ability of stockpiles to contribute to resilience by acting as a buffer in case of temporary supply disruptions has weakened in the last decade.

[4]Own calculation inferred from total stockpile size estimates (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020).

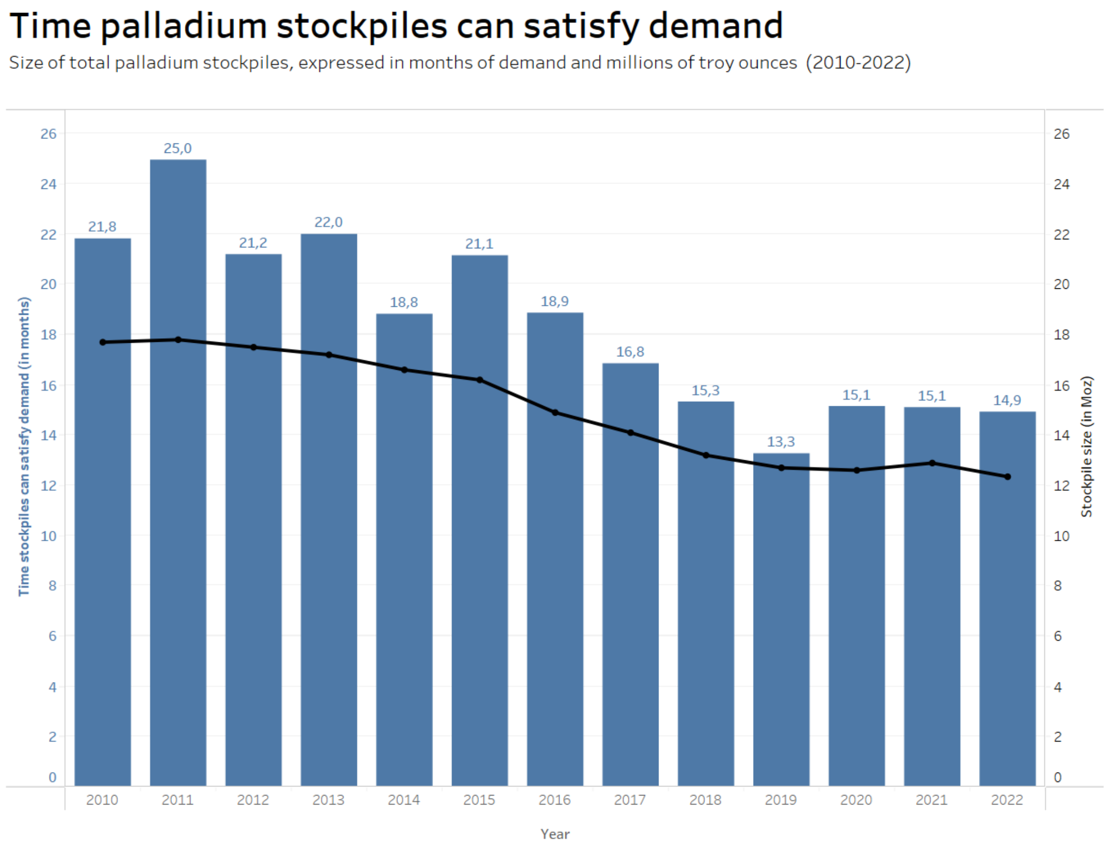

Figure 7.6: Size of total palladium stockpiles at yearend, expressed in months of global palladium demand (in blue) and millions of troy ounces (in black), during the years 2010-2022. Size in Moz for the years 2010-2019 and 2020-2022 retrieved from Bloomberg (Mazneva and Pakiam, 2020) and Reuters (Hobson and Harvey, 2023; Patel and Shivaprasad, 2023), respectively. Time stockpiles can satisfy demand based on own calculations using annual global demand retrieved from Johnson Matthey (2023a).

7.10.2. Total stockpile allocations

Annual total palladium stockpile allocations are inferred from the estimated total palladium stockpile size (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020) identified in the previous subsection. Figure 7.7 shows the annual impact of total stockpile allocations on the palladium market balance during the years 2011-2022.

The estimated total stockpile allocations indicate that stockpile releases have promoted resilience during the years 2012-2022 by significantly mitigating the structural market deficit. During the years 2012-2022, the palladium market experienced a structural market deficit (Cowley and Ryan, 2023). Figure 7.7 shows that during almost all of these years significant stockpile releases occurred, thereby contributing to mitigation of the market deficits. The mitigating effect of these stockpile releases is arguably also reflected in the palladium price (Cowley and Ryan, 2023). The palladium price increased dramatically only from 2018 onwards, despite a structural market deficit since 2012.

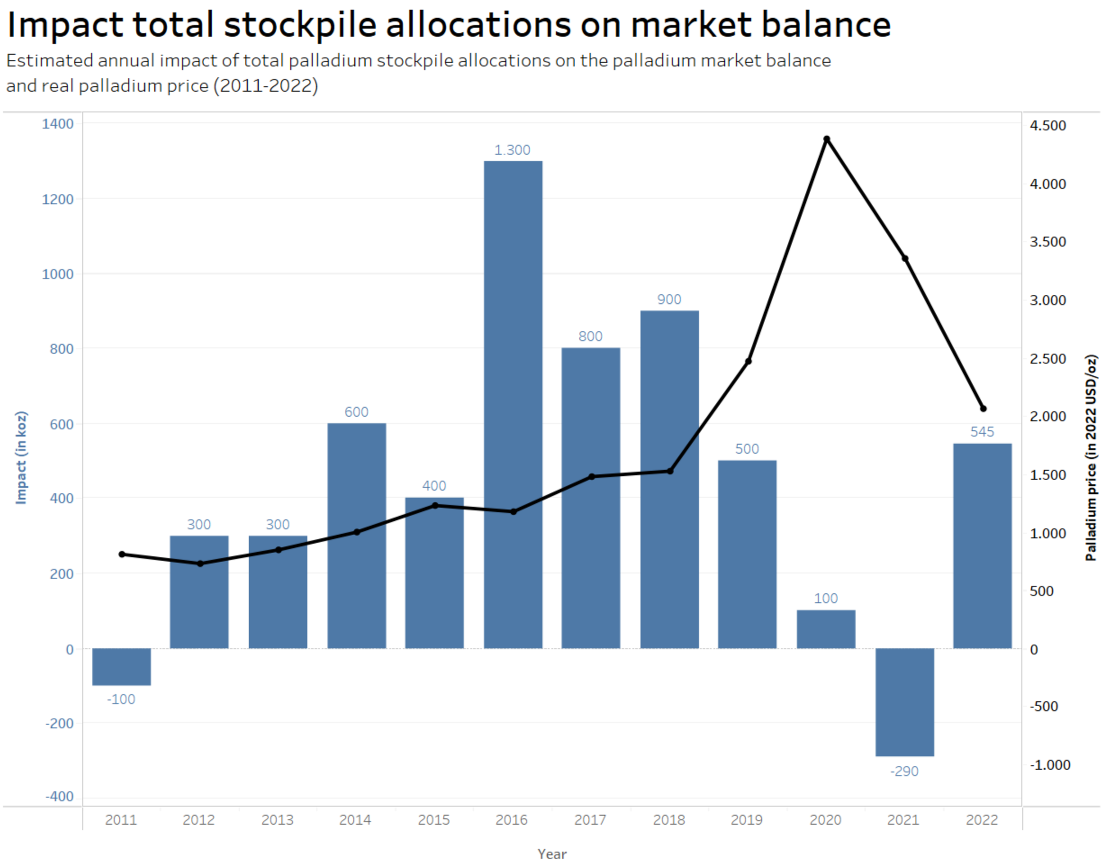

Figure 7.7: Estimated annual impact of total palladium stockpile allocations on the market balance in thousands of troy ounces (in blue) and annual average real palladium price in 2022 US dollars per troy ounce (in black) for the years 2011-2022. Note that a positive impact indicates a stockpile sale that raises the market balance and a negative impact indicates a stockpile acquisition that reduces the market balance. Total palladium stockpile allocations are inferred from identified total stockpile size estimates (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020). Real palladium price based on nominal palladium prices (Macrotrends, 2023) adjusted for inflation using the Commodity Price Index (World Bank, 2023b).

7.10.3. Palladium stockpiling and price

The concurrent trends of an increasing palladium price and declining total palladium stockpiles identified in the previous subsection suggest that palladium price increases incentivise stockpile releases. The concurrent trends found in the previous subsection provide insight into the fourth price feedback loop. Recall that the fourth price feedback loop concerns the effect of the palladium price on palladium stockpiles. The fourth price feedback loop is visualised in Figure 7.8 in dark blue.

Regression analysis indicates that the fourth price feedback loop is negative. To quantify the fourth price feedback effect, logged total palladium stockpile size is regressed on logged real palladium price for the years 2010-2022. The regression results are shown in Table 7.5. The coefficient estimate of logged palladium price is -0.224***. This indicates that a 1%-increase in palladium price is associated with a 0.224%-decrease in total palladium stockpiles, on average. This finding implies that the fourth price feedback loop is negative and that palladium price increases have historically incentivised stockpile releases.

7.11. Interplay stockpiling and price mechanisms

The previous sections indicated a lack of transparency regarding palladium stockpiling, which creates a situation of asymmetric information in the palladium market. It was found that reliable information about palladium stockpiles held by government agencies, companies, and investors is typically not publicly disclosed for strategic purposes. Palladium stockpiles held by ETF investors are an exception, because equity market regulations require ETFs to publicly disclose their holdings. The result of this

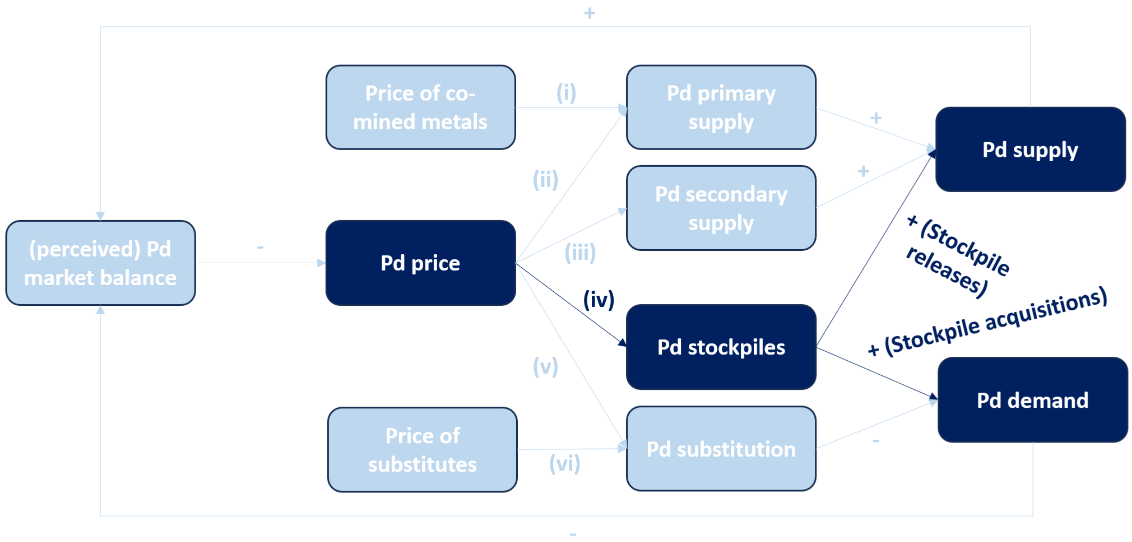

Figure 7.8: Conceptual model of the main price feedback loops in the palladium supply chain. Following System Dynamics convention, plus (+) and minus (-) signs between a factor A and factor B indicate that the factors move in the same direction or opposite direction, respectively (Bala et al., 2017). Pd refers to palladium. The six main price feedback loops are indicated by Roman numerals. The fourth price feedback loops is highlighted in dark blue. Note that stockpiles can either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). Feedback loops based on Sprecher et al. (2015) and Van den Brink et al. (2022, see supplement).

Intercept (standard error)	11.236*** (0.225)
ln(Pd price) (standard error)	-0.224*** (0.031)
Number of observations	13
R^2	0.827
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.095)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.076)
Normal residuals (p-value Shapiro-Wilk test)	Yes (0.257)

Table 7.5: Regression results of regressing logged total palladium stockpile size on logged real palladium price. Underlying data covers the years 2010-2022. *ln(Pd price)* refers to logged real palladium price (in 2022 US dollars/oz). The 95%-confidence interval for this coefficient estimate ranges between -0.292 and -0.156. Note that *** indicates that the coefficient estimates are statistically significant at a 1%-significance level. Own calculations based on palladium stockpile estimates retrieved from Bloomberg and Reuters (Hobson and Harvey, 2023; Mazneva and Pakiam, 2020; Patel and Shivaprasad, 2023) and real nominal palladium prices (Macrotrends, 2023) adjusted for inflation using the Commodity Price Index (World Bank, 2023b).

lack of transparency in palladium stockpile reporting is an (intentional) data gap concerning (i) the specific actors that hold palladium stockpiles, (ii) the size of the stockpiles held by these actors, and (iii) the impact of stockpile allocations on the overall palladium market (balance). The lack of transparency regarding palladium stockpiling creates a situation in which the actor holding the stockpile has more information than other actors in the market, i.e. a situation of asymmetric information.

This lack of transparency regarding palladium stockpiling is problematic from a resilience perspective, because it enables actors that hold palladium stockpiles with an opportunity to manipulate the palladium market. In particular, Russia may historically have used stockpiling to consolidate its dominant position in the palladium market. Recall from Section 7.2 that significant Russian state palladium stockpile sales were found to have suppressed palladium prices during the first decade of this century. Arguably, Russia used these palladium stockpile releases with the intent to make other (non-Russian) palladium-producing operations less profitable. In this regard, it is interesting to note that in 2017-2018, approximately 20% of PGM operations were still loss-making (Alexander et al., 2019), even though the palladium price had already significantly increased compared to the first decade of this century. As a result of this economic strategy, Russia arguably consolidated its dominant position in the global palladium market. Indeed, similar economic strategies have been observed in other commodity markets. In the oil market, OPEC-member Saudi Arabia has historically used temporary oil production increases to make other oil-producing operations less profitable and consolidate its dominant position in the global oil market (Singh, 2020). Such market consolidation is undesirable from a diversity of supply perspective.

Moreover, the lack of transparency regarding palladium stockpiling is problematic from a resilience perspective, because it hinders proper functioning of the price mechanism. The asymmetry of information makes it more difficult for palladium market participants to agree on a common palladium price that accurately reflects the palladium supply-demand balance. Illustratively, the uncertainty regarding arbitrary releases from the Russian state palladium stockpile has historically contributed to palladium price volatility (Risk and Policy Analysts Ltd., 2012). The lack of transparency regarding palladium stockpiling thus leads to asymmetry of information, which complicates the palladium price discovery process. That is, the asymmetric information in the market creates a disconnect between actual and apparent market activity, which ‘delays the deployment of private capital to profitable or promising [⋯] projects, resulting in inefficient use of capital’ (The White House, 2021, p. 190). Hence, the opacity regarding palladium stockpiling arguably has a negative impact on resilience in the palladium supply chain, because it hinders the operation of the price mechanism. Indeed, a functional price mechanism requires a transparent market (Sprecher et al., 2017). Accordingly, more transparency regarding palladium stockpiling is expected to result in a more favourable palladium price discovery process (Rapoza, 2012).

7.12. Chapter conclusion

This chapter investigated how the stockpiling mechanism has changed over time and how this has affected resilience in the palladium supply chain. To that end, two indicators were considered: (i) the time palladium stockpiles can satisfy societal palladium demand when regular supply sources are disrupted and (ii) stockpile allocations.

It was found that the lack of transparency regarding palladium stockpiling is problematic from a resilience perspective. Stockpile actors, sizes, and allocations are often intentionally not disclosed, with the exception of palladium ETFs. The lack of transparency enables stockpiling actors to manipulate the palladium market. In particular, Russia may historically have used palladium stockpile releases to make non-Russian palladium operations less profitable and consolidate its dominant position in the palladium market.

Relatedly, it was found that the opaque nature of palladium stockpiling negatively affected long-term resilience by hindering proper functioning of the price mechanism. Russian state palladium stockpile sales were found to have had a positive impact on short-term resilience by raising the market balance on an annual basis. However, it was found that Russian state stockpile sales suppressed prices during the first decade of this century, thereby inhibiting expansion of regular supply sources. This likely contributed to the structural market deficit in the subsequent decade. This finding illustrates the trade-off between short-term desirability for resilience and long-term desire for system change (Sprecher et al., 2015).

Furthermore, it was found that palladium stockpiling has historically both positively and negatively affected resilience, depending on the strategy and position of the stockpiling actor. On the hand, for example, strategic state stockpile sales by the US contributed to resilience during the late 1990s and early 2000s. On the other hand, speculative palladium stockpiling by car companies aggravated the market deficit and price spike during the turn of the century. This finding is in line with Van de Camp (2020), who found that the effect of stockpiling on resilience depends on the position and strategy of the actor who holds the stockpile.

Moreover, it was found that a decline in total palladium stockpiles since 2010 reduced the buffering capacity of the stockpiling mechanism in case of future temporary supply disruptions. Total palladium stockpiles were found to have decreased by approximately 31.7% from 21.8 months of global demand in 2010 to 14.9 months in 2022. The decline was found to be primarily attributable to stockpile releases by the Russian state and ETFs rather than company stockpiling.

Lastly, it was found that significant palladium stockpile sales contributed to resilience by mitigating the structural market deficit during the years 2012-2022. It was found that an increasing palladium price incentivised significant palladium stockpile sales during the years 2012-2022. More specifically, regression analysis indicated that a 1%-increase in palladium price is associated with a 0.224%-decrease in total palladium stockpiles, on average.

8 The substitution mechanism

In this chapter, it is investigated how the substitution mechanism has changed over time and how this has affected the palladium supply chain's resilience. This chapter relates to the second sub-question: *How have the four resilience mechanisms changed over time, and what do these changes imply for resilience?*

8.1. Introduction

The substitution mechanism concerns the switching mechanism in which either the overall technology used in an end-product or the material used is replaced. Substitution can contribute to resilience by lowering material demand (Sprecher et al., 2015). If a material's substitutes become relatively less expensive, this can incentivise increased substitution, thereby reducing material demand (Nassar, 2015; Sprecher et al., 2015; Van den Brink et al., 2022). Recall from Chapter 4 that this price-related substitution is captured by the fifth and sixth price feedback loops. Accordingly, this chapter's analysis of the substitution mechanism focuses on the fifth and sixth price feedback loops. These price feedback loops are visualised in Figure 8.1 in dark blue.

The fifth price feedback loop concerns the effect of the palladium price on palladium demand through substitution. This price feedback effect can be quantified using the price elasticity of demand. The sixth price feedback loop concerns the effect of the price of palladium's substitutes on palladium demand through substitution. This price feedback effect can be measured using the cross price elasticity of demand.

Accordingly, to investigate the temporal dynamics of the substitution mechanism, the substitution mechanism was operationalised in Chapter 4 based on two indicators: (i) the price elasticity of demand and (ii) the cross price elasticity of demand. Recall that the first indicator measures the responsiveness of palladium demand to changes in the palladium price. A price elasticity of demand between 0 and -1 indicates inelastic demand and limited substitution, for example due to a lack of suitable substitutes (Nassar, 2015). A price elasticity of demand more negative than -1 indicates elastic demand and frequent substitution, suggesting the availability of suitable substitutes (Nassar, 2015). The regression-estimated price elasticity of demand is used as a proxy for the first indicator. Moreover, recall that the second indicator measures the responsiveness of palladium demand to changes in the price of another material. Positive cross price elasticity implies that this other material acts as a substitute (to palladium), whereas negative cross price elasticity implies that this material acts as a complement (to palladium) (Fizaine, 2022; Nassar, 2015).

An overview of this operationalisation of the substitution mechanism is provided in Table 8.1.

The remainder of this chapter consists of three sections. First, Section 8.2 introduces the regression approach used to estimate the (cross) price elasticities of demand. Subsequently, Section **??** discusses palladium substitution by application based on the estimated (cross) price elasticities. Finally, Section 8.4 summarises this chapter's findings.

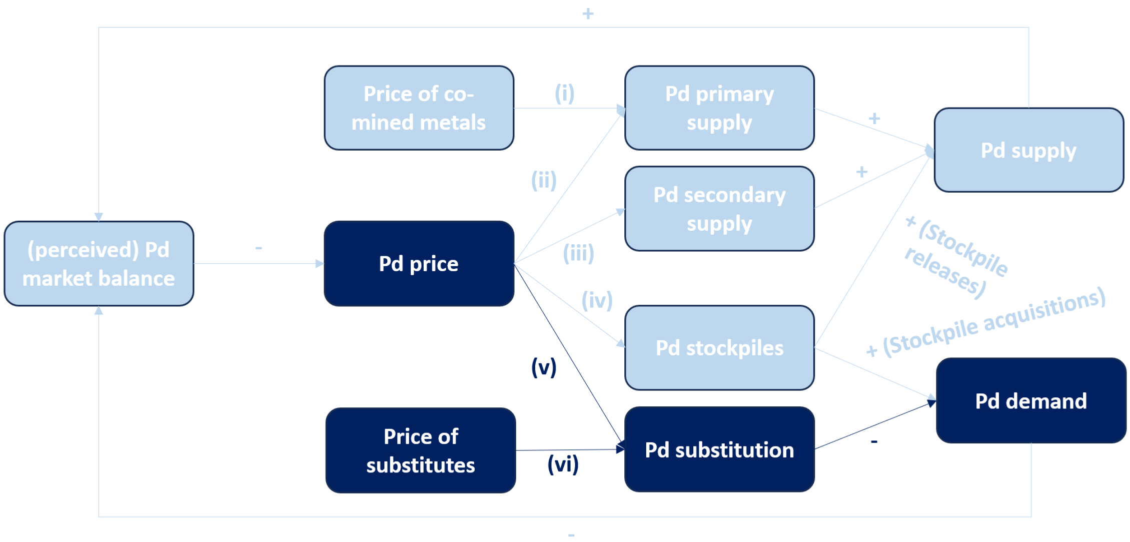

Figure 8.1: Conceptual model of the main price feedback loops in the palladium supply chain. Following System Dynamics convention, plus (+) and minus (-) signs between a factor A and factor B indicate that the factors move in the same direction or opposite direction, respectively (Bala et al., 2017). Pd refers to palladium. The six main price feedback loops are indicated by Roman numerals. The last two price feedback loops are highlighted in dark blue and are investigated in this chapter. Note that stockpiles can either be used for demand-raising speculative stockpile acquisitions or supply-raising stockpile releases (Sprecher et al., 2015; Van de Camp, 2020). Feedback loops based on Sprecher et al. (2015) and Van den Brink et al. (2022, see supplement).

Indicator	Proxy	Data sources
Price elasticity of demand	Regression-estimated price elasticity of demand	Johnson Matthey (2023a)
		Macrotrends (2023)
		World Bank (2023b)
Cross price elasticity of demand	Regression-estimated cross price elasticity of demand	Johnson Matthey (2023a)
		World Bank (2023b)

Table 8.1: Overview of the operationalisation of the substitution mechanism.

8.2. Regression approach: (cross) price elasticities of demand

Price elasticities are commonly estimated using a log-log linear regression model (Holmes et al., 2017). Accordingly, Nassar used log-log linear regression models to estimate the (cross) price elasticity of demand by palladium application (Nassar, 2015, see supplement). This thesis applies similar log-log linear regression models to estimate these (cross) price elasticities (for the mathematical regression equations, see Appendix E.2). More specifically, logged palladium demand is regressed on the logged real palladium price and the logged real price of palladium's substitutes. Four potential substitutes of palladium identified by Nassar (2015) are considered: platinum, nickel, gold, and silver. Following Nassar (2015), two additional non-price explanatory variables are considered in the regression analyses to improve model accuracy: (logged) global real GDP and (logged) palladium demand in the previous year. Global GDP is considered as an additional explanatory variable, because economic development is an important driver of metal demand (Moszkowicz, 2017). Palladium demand in the previous year is considered as an additional explanatory variable, because the inclusion of a lagged dependent variable in the model can help account for autocorrelation when using time-series data (Wilkins, 2018). In total, seven explanatory variables are thus considered to estimate palladium demand (by application). Obviously many more factors influence palladium demand, but modelling those is beyond the scope of this analysis.

The regression analyses in this chapter improve on the approach by Nassar (2015) in two main ways. First, this study's regression approach is more transparent about the statistical testing of the validity of the regression results. Second, the regression analyses in this study are based on longer time-series data, also covering recent years.

Similar to Chapter 6, the regression analyses are conducted using the Statsmodels library (Seabold and Perktold, 2010) in Python. Annual palladium demand data by application is retrieved for the years 1980-2022 from Johnson Matthey (2023a). Nominal prices of palladium (Macrotrends, 2023), platinum, nickel, gold, and silver (World Bank, 2023b) are retrieved and adjusted for inflation based on the Commodity Price Index (World Bank, 2023b). Annual real global GDP (in constant 2015 US dollars) is retrieved from the World Bank (2023a).

Estimation of the (cross) price elasticities of demand is attempted for seven palladium demand categories: autocatalysts, chemical, dental and biomedical, electronics, jewellery, other applications, and overall demand (Johnson Matthey, 2023a). The regression results are considered statistically significant and reliable if (i) the estimated coefficients are statistically significant at a 10% significance level (or better) and (ii) the assumptions of linear regression are not grossly violated. Similar to the regression approach used in Chapter 6, the following assumptions of linear regression are statistically tested: (i) the residual errors should be independent, (ii) the residual errors should be homoscedastic, and (iii) the residual errors should be normally distributed (Date, n.d.; Greene, 2012). In addition to these assumptions, the multicollinearity between the explanatory variables is again considered.

Again, assumptions (i), (ii), and (iii) are considered satisfied if the Breusch-Godfrey, Breusch-Pagan, and Shapiro-Wilk tests are passed at a 5% significance level, respectively. Furthermore, a condition number above 1000 is again considered as indicative of strong multicollinearity and model instability (Chen,

Note that, unlike the estimation of the (cross) price elasticities of supply in Chapter 6, only non-lagged prices are used to estimate the (cross) price elasticities of demand in this chapter. That is, the estimated (cross) price elasticities of demand presented in this chapter concern short-term price elasticities, reflecting the responsiveness of demand to price changes within the same year.

8.3. Regression results: (cross) price elasticities of demand by application

This section investigates how palladium substitution has evolved over time using the (cross) price elasticities of demand. To evaluate palladium's substitutability, the European Commission (2023c) distinguishes between six palladium application areas: autocatalysts (88%), chemical (3%), electronics (4%), dental (2%), jewellery (2%), and others (1%). Similarly, this study retrieves demand data from Johnson Matthey (2023a) for seven palladium demand categories: autocatalysts, chemical, dental and biomedical, electronics, jewellery, others, and overall demand. These application areas are discussed in the subsections below. Following econometric convention (Imbens, 2021), the significance levels of the estimated (cross) price elasticities are denoted by one, two, or three asterisks for 10% (*), 5% (**), and 1% (***), respectively. For interpretation purposes, the explanatory variables are abbreviated in the reported regression results: logged real palladium price (in 2022 US dollars/oz) (*ln(Pd price)*), logged real platinum price (in 2022 US dollars/oz) (*ln(Pt price)*), to logged real nickel price (in 2022 US dollars/metric tonne) (*ln(Ni price)*), logged real gold price (in 2022 US dollars/oz) (*ln(Au price)*), and logged real silver price (in 2022 US dollars/oz) (*ln(Ag price)*).

8.3.1. Automotive applications

Palladium's most common application is in automotive catalytic converters, often referred to as autocatalysts, used in internal combustion engine vehicles (ICEVs) (Cowley and Ryan, 2023; European Commission, 2023c). More specifically, palladium aids as a chemical catalyst that reduces pollutant emissions of hydrocarbons and carbon monoxide (DeCarlo and Goodman, 2022; Nassar, 2015).

Despite decades of autocatalyst research, no suitable non-PGM substitutes for palladium have been identified (Nassar, 2015; SFA Oxford, 2017). For example, base metal catalysts (e.g. containing copper) were found to lose most of their reactivity after several weeks of use due to the extremity of autocatalyst operating conditions (Nassar, 2015; SFA Oxford, 2017). The only suitable substitute for palladium is platinum, which is equally effective at reducing pollutant emissions in autocatalysts (Nassar, 2015;WPIC, 2022). In fact, when vehicle emission regulations were first introduced (e.g. Clean Air Act in the US) in the 1970s and 1980s, platinum rather than palladium was initially used in autocatalysts (WPIC, 2022). The reason for this is that fossil fuels then had a relatively high sulphur content, which reduces palladium's catalytic efficiency (Nassar, 2015;WPIC, 2022). For this reason, twice as much palladium than platinum was required to achieve the same emission-reducing effects (WPIC, 2022).

However, the reduction of sulphur content in fossil fuels since the early 2000s changed the substitution ratio between palladium and platinum from 2:1 to 1:1 (WPIC, 2022). Accordingly, producers' choice between the two PGMs has become predominantly based on the palladium-platinum price differential (Nassar, 2015; SFA Oxford, 2017). Since the turn of the century, palladium has typically been cheaper than platinum and has therefore been autocatalyst producers' metal of choice (Hagelüken et al., 2005; SFA Oxford, 2017). During periods when palladium was more expensive than platinum, e.g. during the substantial palladium market deficits in 2000 and 2022, palladium was in turn partially substituted by platinum (SFA Oxford, 2023d;WPIC, n.d., 2022).

The brief literature review above indicates that material substitution of palladium in autocatalysts has historically been conditional on the palladium market deficit being sufficiently large to raise the palladium price above the platinum price. This suggests that not the absolute palladium price or palladium market deficit per se, but rather the palladium-platinum price differential is an important driver of palladium substitution in autocatalysts (SFA Oxford, 2017). Accordingly, the (logged) palladium-platinum price ratio is considered as an additional explanatory variable to estimate autocatalyst palladium demand.

The conducted regression analyses of the (cross) price elasticities suggest that substitution has historically not significantly affected autocatalyst palladium demand in the short term (i.e. within the same year). It was attempted to estimate the (cross) price elasticities of autocatalyst palladium demand. None of the possible combinations of the eight explanatory variables resulted in regression results that had significant coefficients for all explanatory variables and passed the Breusch-Godfrey and Breusch Pagan tests (for details, see Appendix E.3). That is, the conducted regression analyses did not result in reliable and statistically significant (cross) price elasticities. The statistical insignificance of the price-related explanatory variables suggests that non-price factors are the primary drivers of autocatalyst palladium demand in the short term. In particular, vehicle emission regulations may be more dominant than price factors in determining palladium demand (Hughes et al., 2021; Nassar, 2015). For policy-makers, this finding suggests that vehicle emission regulation policy may be more effective at reducing (autocatalyst) palladium demand than substitution-promoting policy in the short term. These policy implications are further discussed in Chapter 9.

Accordingly, the regression results by Nassar (2015) suggest that platinum has historically acted as a complement rather than a substitute to palladium in autocatalysts in the short term. Nassar (2015) obtained a cross price elasticity of autocatalyst palladium demand with respect to platinum of -0.29**. This negative cross price elasticity implies that platinum has historically acted as a complement to palladium in autocatalysts in the short term. Indeed, autocatalysts in diesel cars often contain alloys of PGMs to improve efficiency (Renner et al., 2018; SFA Oxford, 2017). One possible explanation for the fact that platinum acts as a complement rather than a substitute within the same year is the time delay between a price increase and the implementation of substitution. To switch between palladium and platinum, autocatalyst producers require a lead time of 6-18 months for retooling and reprocessing (Safirova et al., 2017; Van der Walt and Pakiam, 2019).

8.3.2. Chemical applications

Due to its superior catalytic properties, palladium is used as a process catalyst in chemical processes (Nassar, 2015; Renner et al., 2018). For example, palladium is the most commonly used catalyst for the production of hydrogen peroxide and acetaldehyde (Nassar, 2015). Alternative catalysts are available, but often have lower technical performance than palladium (Nassar, 2015; SFA Oxford, 2017). Moreover, substitution is disincentivised by the fact that catalyst replacement often requires significant time and economic investment for adapting the entire chemical process infrastructure (Nassar, 2015; SFA Oxford, 2017). Accordingly, metal research organisation SFA Oxford (2017) reported that palladium demand for chemical applications is inelastic.

The conducted regression analyses of the (cross) price elasticities suggest that substitution has historically not significantly affected chemical palladium demand in the short term (i.e. within the same year). It was attempted to estimate the (cross) price elasticities of chemical palladium demand. None of the possible combinations of the seven explanatory variables resulted in regression results that had significant coefficients for all explanatory variables and passed the Breusch-Godfrey and Breusch Pagan tests (for details, see Appendix E.4). That is, the conducted regression analyses did not result in reliable and statistically significant (cross) price elasticities. This implies that price factors have historically not significantly affected chemical palladium demand in the short term.

8.3.3. Dental and biomedical applications

Palladium is used as an alloy in dental and biomedical applications due to its desirable properties, such as high corrosion resistance and bio-compatibility (Encyclopaedia Britannica, 2023). In particular, palladium is often used in tooth conserving dentistry (e.g. tooth fillings) and prosthetic dentistry (e.g. crowns and bridges) (Hagelüken et al., 2005; Rushforth, 2004). For these applications, both precious-metals-based alloys and non-precious-metals-based alloys are available (Hagelüken et al., 2005; Rushforth, 2004). The most commonly used precious-metals-based alloys include gold-based alloys and palladium-based alloys (Rushforth, 2004). Palladium is used in 90% of these dental precious-metals alloys (Hagelüken et al., 2005; Nassar, 2015). Non-precious-metals alloys include nickel-chromium, cobalt-chromium, and ceramics alloys (Rushforth, 2004). The palladium market deficit and associated price spike around the year 2000 incentivised limited substitution of palladium-based alloys by non-precious-metals alloys (Rushforth, 2004). However, precious-metals alloys have remained the preferred material for dental applications, despite being significantly more expensive than non-precious-metals alloys (Hagelüken et al., 2005; Rushforth, 2004). This can be explained both by their superior material properties and patients' subjective preference for precious-metals alloys (Hagelüken et al., 2005). In Japan, another factor limiting substitution is the fact that the state insurance programme specifically subsidises palladium-gold alloys (Nassar, 2015; SFA Oxford, 2017).

In line with the above, the estimated price elasticity suggests that substitution has historically only slightly reduced dental and biomedical palladium demand in the short term. Logged dental and biomedical palladium demand is regressed on logged palladium price and logged previous-year dental and biomedical palladium demand. The regression results are shown in Table 8.2. The estimated coefficient of logged palladium price is -0.109***. This indicates that a 1%-increase in palladium price is associated with a 0.109%-decrease in dental and biomedical palladium demand within the same year, on average, ceteris paribus. The price elasticity value is similar to the -0.16*** reported by Nassar (2015). The estimated price elasticity indicates that, in the short term, dental and biomedical demand for palladium is expected to negatively respond to palladium price increases, but is very inelastic. This implies that substitution has historically only slightly reduced palladium demand for dental and biomedical applications in the short term. Accordingly, Nassar (2015) found a cross price elasticity of dental palladium demand with respect to nickel of -0.08**. This negative cross price elasticity suggests that nickel-based alloys act as complements rather than significant substitutes to palladium in dental applications in the short term.

Intercept	0.924*** (0.319)
Ln(Pd price)	-0.109*** (0.020)
Ln(previous year demand)	0.963*** (0.035)
Number of observations	42
R^2	0.970
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.707)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.318)
Normal residuals (p-value Shapiro-Wilk test)	No (0.002)
Strong multicollinearity (condition number)	No (212)

Table 8.2: Regression results for estimating the price elasticity of palladium demand for dental and biomedical applications. The 95%-confidence interval for the coefficient of logged palladium price ranges between -0.151 and -0.068. The explanatory variable *ln(previous year demand)* refers to logged dental and biomedical palladium demand in the previous year (in koz).

Palladium being more expensive than gold could incentivise more substitution of palladium-based alloys for gold-based alloys, thereby reducing palladium demand (SFA Oxford, 2017). However, these gold-based alloys still comprise of palladium for around 8% (Rushforth, 2004). Moreover, gold has typically been more expensive than palladium historically (see Figure E.1 in Appendix E).

Overall, these findings suggest that substitution has historically only slightly reduced palladium demand in dental and biomedical applications in the short term. Identified reasons for the limited substitution include Japanese government subsidies that disincentivise substitution (Nassar, 2015; SFA Oxford, 2017), substitutes' (perceived) lower quality (e.g., non-precious-metals dental alloys), and substitutes' higher price (e.g., gold-based dental alloys).

8.3.4. Electrical applications

Palladium is used as an adhesion layer in semiconductors (DeCarlo and Goodman, 2022; Nassar, 2015). More specifically, palladium is primarily used in multi-layer ceramic capacitors (MLCCs) (Mikkenie, 2011; Nassar, 2015). Since the mid-1990s, palladium-based MLCCs have increasingly been substituted by less expensive nickel- and copper-based MLCCs (Mikkenie, 2011; Nassar, 2015). As a result, the market share of palladium-based MLCCs has significantly declined from 85% in 1997 to 10-15% in the late 2000s (Nassar, 2015). The palladium market deficit and associated price spike around the year 2000 provided an important impetus for this substitution of palladium in electronics (SFA Oxford, 2017). In recent years, this substitution has continued. The high palladium price in recent years as well as the desire to reduce exposure to the palladium supply chain incentivised MLCC-producers to switch from palladium to nickel (Carrara et al., 2023). Consequently, palladium demand for electronics declined by approximately 79% from 2620 koz in 1995 to 544 koz in 2022 (Johnson Matthey, 2023a). In recent years, palladium-based MLCCs have predominantly been used in electrical applications that require a high degree of reliability, e.g. in aerospace and military applications (Nassar, 2015; Renner et al., 2018).

The estimated price elasticity suggests that substitution has historically only slightly reduced electronics palladium demand in the short term (i.e. within the same year). Logged electronics palladium demand is regressed on logged palladium price and logged electronics palladium demand in the previous year. The regression results are shown in Table 8.3. The estimated coefficient of logged palladium price is -0.137***. This indicates that a 1%-increase in palladium price is associated with a 0.137%-decrease in electronics palladium demand within the same year, on average, ceteris paribus. The price elasticity value is similar to the -0.19** reported by Nassar (2015). The price elasticity estimate indicates that, in the short term, electronics palladium demand is expected to negatively respond to palladium price increases, but is very inelastic.

Intercept	2.267*** (0.641)
Ln(Pd price)	-0.137*** (0.039)
Ln(previous year demand)	0.805*** (0.076)
Number of observations	42
R^2	0.786
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.195)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.090)
Normal residuals (p-value Shapiro-Wilk test)	No (0.000)
Strong multicollinearity (condition number)	No (203)

Table 8.3: Regression results for estimating the price elasticity of palladium demand for electrical applications. The 95%-confidence interval for the coefficient of logged palladium price ranges between -0.216 and -0.058. The explanatory variable *ln(previous year demand)* refers to logged electronics palladium demand in the previous year (in koz).

Interestingly, the brief literature review indicated significant substitution of palladium-based MLCCs since the mid-1990s, whereas the price elasticity indicated a limited demand-reducing effect of substitution. This apparent contradiction can be explained by the fact that MLCCs in high-end applications account for approximately half of electronics palladium demand (SFA Oxford, 2017). The price elasticity estimate thus signals that substitution of palladium in these high-end applications is limited, reflecting users' limited willingness to switch to lower-reliability substitutes.

8.3.5. Jewellery applications

Palladium is used as an alloying metal in jewellery due to its desirable properties, such as high corrosion resistance and a relatively high melting point (Encyclopaedia Britannica, 2023). In particular, palladium provides the primary bleaching effect in so-called white gold (Nassar, 2015). Nickel-based white gold can be used as a less expensive alternative to palladium-based white gold (Hagelüken et al., 2005). However, the use of nickel in white gold has several disadvantages, such as reduced recyclability, susceptibility to fire cracking, and poor workability (Nassar, 2015). Moreover, wearing white gold with high nickel content can cause undesirable allergic reactions (Hagelüken et al., 2005; Nassar, 2015). Hence, these considerations make palladium-based white gold more desirable than nickel-based white gold (Encyclopaedia Britannica, 2023). Another reason why jewellery demand for palladium might be relatively inelastic is that the price of palladium only accounts for a small part of the price of the final end-products. Moreover, jewellery are luxury goods and high palladium prices may actually incentivise jewellery demand for palladium (SFA Oxford, 2017).

In line with the above, palladium demand for jewellery applications is found to be very inelastic in the short term (i.e. within the same year). Logged jewellery palladium demand is regressed on logged palladium price and logged jewellery palladium demand in the previous year. The regression results are shown in Table 8.4 (see Model 1). The estimated coefficient of logged palladium price is -0.105**. This indicates that a 1%-increase in palladium price is associated with a 0.105%-decrease in jewellery demand within the same year, on average, ceteris paribus. Similarly, Nassar (2015) found a price elasticity of jewellery palladium demand of -0.63*. The price elasticity estimate indicates that, in the short term, jewellery demand for palladium is expected to negatively respond to palladium price increases, but is very inelastic.

Moreover, it is found that silver and gold have historically acted as complements and platinum as a substitute for palladium in jewellery applications in the short term. In addition to the price elasticity of jewellery palladium demand, reliable and statistically significant cross price elasticities of jewellery palladium demand with respect to silver, gold, and platinum are obtained. Logged jewellery palladium demand is regressed on logged silver price and logged jewellery palladium demand in the previous year. The regression results are shown in Table 8.4 (see Model 2). The estimated coefficient of logged silver price is -0.372***. The negative cross price elasticity with respect to silver indicates that silver acts as a complement to palladium in jewellery applications in the short term. Additionally, logged jewellery palladium demand is regressed on logged gold price, logged platinum price, and logged jewellery palladium demand in the previous year. The regression results are shown in Table 8.4 (see Model 3). The estimated coefficients of logged gold price and logged platinum price are -0.497*** and 0.377**, respectively. These cross price elasticities indicate that, in the short term, gold and platinum have historically acted as complement and substitute to palladium, respectively. Indeed, platinum alloys can be used as an alternative to palladium-based white gold (Hagelüken et al., 2005).

Model	**1**	**2**	**3**
Intercept	1.114** (0.538)	1.385*** (0.431)	1.823** (0.835)
Ln(Pd price)	-0.105** (0.051)	-	-
Ln(Pt price)	-	-	0.377** (0.169)
Ln(Ag price)	-	-0.372*** (0.101)	-
Ln(Au price)	-	-	-0.497*** (0.117)
Ln(previous year demand)	0.918*** (0.062)	-	0.815*** (0.068)
Number of observations	42	42	42
R^2	0.868	0.892	0.903
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.219)	Yes (0.583)	Yes (0.384)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.930)	Yes (0.519)	Yes (0.065)
Normal residuals (p-value Shapiro-Wilk test)	No (0.000)	No (0.000)	No (0.000)
Strong multicollinearity (condition number)	No (118)	No (79)	No (285)

Table 8.4: Regression results for estimating the (cross) price elasticities of palladium demand for jewellery applications. The 95%-confidence interval for the coefficient of logged palladium price ranges between -0.208 and -0.001. The explanatory variable *ln(previous year demand)* refers to logged jewellery palladium demand in the previous year (in koz).

Nassar (2015) additionally found a cross price elasticity of jewellery palladium demand with respect to nickel of 0.89***. This positive cross price elasticity indicates that nickel has historically acted as a substitute to palladium in jewellery applications in the short term. This reflects that indeed nickel-based white gold can act as a substitute to palladium-based white gold.

Overall, it is found that substitution has historically only slightly reduced palladium demand for jewellery applications in the short term. Platinum and nickel are identified as substitutes, whereas silver and gold are identified as complements to palladium in the short term. Identified reasons for the limited demand-reducing effect of substitution include substitutes' lower technical performance (e.g., workability) and subjective consumer preference for palladium-based white gold.

8.3.6. Other applications

Besides the applications discussed above, palladium is also used in numerous other applications. These include, amongst others, stationary pollution control and oxygen sensors in internal combustion engines (Hagelüken et al., 2005; Johnson Matthey, 2023a). These are not discussed in further detail here, because they only account for a very small fraction (1%) of overall palladium demand (European Commission, 2023c). However, the (cross) price elasticities are estimated to evaluate the overall substitutability of palladium in these remaining applications.

The estimated price elasticity suggests that substitution has historically only slightly reduced palladium demand for other applications in the short term (i.e. within the same year). Logged palladium demand for other applications is regressed on logged palladium price, logged platinum price, and logged silver price. The regression results are shown in Table 8.5 (see Model 1). The estimated coefficient of logged palladium price is -0.237***. That is, a 1%-increase in palladium price is associated with a 0.237% decrease in palladium demand for other applications within the same year, on average, ceteris paribus. This price elasticity estimate indicates that, in the short term, palladium demand for other applications is expected to negatively respond to palladium price increases, but is very inelastic.

Moreover, it is found that silver has historically acted as a substitute, whereas platinum, gold, and, nickel have historically acted as complements to palladium in other applications in the short term. The regression mentioned above (i.e. Model 1) results in cross price elasticities of palladium demand for other applications with respect to platinum and silver of -1.100*** and 0.681***, respectively. The estimate for the cross price elasticity with respect to platinum is similar to the -0.63*** found by Nassar (2015). The negative cross price elasticity with respect to platinum indicates that platinum has historically acted as a complement to palladium in other applications in the short term. The positive cross price elasticity with respect to silver indicates that silver has historically acted as a substitute to palladium in other applications in the short term. Furthermore, logged palladium demand for other applications is regressed on logged silver price, logged gold price, and logged nickel price. The regression results are shown in Table 8.5 (see Model 2). The estimates for the cross price elasticities of palladium demand for other applications with respect to silver, gold, and nickel are 1.044***, -1.024***, and -0.503***, respectively. The positive cross price elasticity with respect to silver again indicates that silver has historically acted as a substitute to palladium in other applications in the short term. The negative cross price elasticities with respect to gold and nickel indicate that gold and nickel have historically acted as complements to palladium in the short term.

Model	**1**	**2**
Intercept	12.171*** (1.323)	13.887*** (1.527)
Ln(Pd price)	-0.237*** (0.085)	-
Ln(Pt price)	-1.100*** (0.210)	-
Ln(Ag price)	0.681*** (0.178)	1.044*** (0.297)
Ln(Au price)	-	-1.024*** (0.275)
Ln(Ni price)	-	-0.503*** (0.165)
Number of observations	43	43
R^2	0.573	0.539
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.198)	Yes (0.306)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.274)	Yes (0.173)
Normal residuals (p-value Shapiro-Wilk test)	No (0.001)	Yes (0.814)
Strong multicollinearity (condition number)	No (248)	No (339)

Table 8.5: Regression results for estimating the (cross) price elasticities of palladium demand for other applications. The 95%-confidence interval for the coefficient of logged palladium price ranges between -0.410 and -0.064.

8.3.7. Overall demand

The conducted regression analyses of the (cross) price elasticities suggest that substitution has historically not significantly affected overall palladium demand in the short term (i.e. within the same year). It was attempted to estimate the (cross) price elasticities of palladium autocatalyst demand. None of the possible combinations of the seven explanatory variables resulted in regression results that had significant coefficients for all explanatory variables, included at least one price-related explanatory variable, and passed the Breusch-Godfrey and Breusch Pagan tests (for details, see Appendix E.5). Hence, similar to the autocatalyst and chemical demand categories, the conducted regression analyses did not result in reliable and statistically significant (cross) price elasticities. The statistical insignificance indicates that palladium, platinum, nickel, gold, and silver prices have historically not significantly affected overall palladium demand in the short term. The findings thus suggest that non-price factors are more dominant drivers of overall palladium demand. In particular, as stated before, vehicle emission regulations are the biggest drivers of overall palladium demand (Hughes et al., 2021).

The finding above is in accordance with the literature in the sense that no recent price elasticity of overall palladium demand is available in the literature (Safirova et al., 2017). A recent literature review of commodity price elasticities by Fally and Sayre (2018) did identify a price elasticity of overall palladium demand of -0.2 by Burrows (1974). This inelastic price elasticity suggests that substitution has historically only slightly reduced overall palladium demand in the short term. However, this price elasticity is considered severely outdated, as it dates back to the 1970s: a period before palladium became commonplace in autocatalysts (SFA Oxford, 2023d).

Accordingly, the regression results by Nassar (2015) suggest that platinum has historically acted as a complement rather than a substitute to palladium overall in the short term. Nassar (2015) found a negative cross price elasticity of overall palladium demand with respect to platinum of -0.30***. Illustratively, the cross price elasticities with respect to platinum that Nassar (2015) found for overall palladium demand (-0.30***) and autocatalyst palladium demand (-0.29**) are very similar. This can be explained by the fact that autocatalyst palladium demand accounts for over 80% of overall palladium demand (European Commission, 2023c; SFA Oxford, 2023d). Hence, it is unsurprising that this study found a statistically-insignificant price elasticity of overall palladium demand is not surprising, considering that the price elasticity of autocatalyst palladium demand was also found to be statistically insignificant.

The statistical insignificance of the (cross) price elasticities of overall palladium demand found in this study suggests that the fifth and sixth price feedback effects have historically not significantly affected palladium demand in the short term (i.e. within the same year). Possibly, the fifth and sixth price feedback effects do significantly affect overall palladium demand in the longer term. If that were found to be true, that would be in line with Sprecher et al. (2015) and Van den Brink et al. (2022), who use time delays for the fifth and sixth price feedback loops in their conceptual material supply chain models. However, it may be the case that substitution does not significantly affect overall palladium demand even in the longer term, because of a lack of suitable substitutes. Indeed, the brief reviews of substitutes by application suggested that substitute availability and desirability are often limited.

In terms of resilience, the statistical insignificance of the (cross) price elasticities of overall palladium demand suggests that the substitution mechanism has historically not significantly affected demand and, therefore, resilience in the short term. Moreover, it is interesting to note that co-mining of palladium's substitutes with palladium may limit the ability of the substitution mechanism to promote resilience. This chapter identified platinum and nickel as substitutes for some palladium applications. However, recall from the companionality analysis in Chapter 6 that platinum and nickel are often co-mined with palladium. This co-mining limits the ability of the substitutes to act as suitable alternatives in case of a supply disruption, because both the supply of palladium and of its substitutes will likely be affected simultaneously (Nassar, 2015).

8.4. Chapter conclusion

This chapter investigated how the substitution mechanism has changed over time and how this has affected resilience in the palladium supply chain. To that end, two indicators were considered: (i) the price elasticity of demand and (ii) the cross price elasticity of demand. Price and cross price elasticities were estimated for seven palladium demand categories: autocatalysts, chemical, dental and biomedical, electronics, jewellery, other applications, and overall demand. Cross price elasticities of demand were estimated with respect to four potential palladium substitutes: platinum, nickel, gold, and silver.

It was found that substitution has historically not significantly affected autocatalyst, chemical, and overall palladium demand in the short term (i.e. within the same year). The conducted regression analyses for autocatalyst, chemical, and overall demand did not result in reliable and statistically significant (cross) price elasticities. This indicated that autocatalyst, chemical, and overall palladium demand have historically not been significantly affected by price factors in the short term. Vehicle emissions regulations may be more dominant drivers of autocatalyst and, consequently, overall palladium demand in the short term.

Moreover, it was found that substitution has historically only slightly reduced palladium demand for dental and biomedical, electrical, jewellery, and other applications in the short term. The obtained price elasticity estimates for dental and biomedical (-0.109***), electrical (-0.137***), jewellery (-0.105**), and other (-0.237***) indicate that palladium demand has historically negatively responded to palladium price increases, but has been very inelastic in the short term.

Accordingly, it was found that palladium's potential substitutes (platinum, nickel, gold, and silver) have historically mostly acted as complements rather than substitutes in the short term. For jewellery applications, the cross price elasticity estimates indicate that platinum (0.377**) has historically acted as a substitute, whereas gold (-0.497***) and silver (-0.372***) have acted as complements in the short term. For the other applications category, the cross price elasticity estimates indicate that silver (0.681***) has historically acted as a substitute, whereas platinum (-1.100***), nickel (-0.503***), and gold (-1.024***) have acted as complements in the short term.

Overall, it can be concluded that the substitution mechanism has historically not provided much resilience to fast disruptions. After all, it was found that substitution has historically not significantly reduced overall palladium demand in the short term. One explanation for the inelasticity of palladium demand in the short term may be the time delay associated with implementing substitution. Possibly, palladium demand is more elastic and the substitution mechanism's effect on resilience is more positive in the longer term. However, the brief reviews of substitutes by application suggest that the inelasticity of palladium demand likely also results from a lack of suitable substitutes. Substitution of palladium was found to be limited by co-mining of substitutes with palladium; Japanese government subsidies for palladium-based dental alloys; subjective consumer preference (e.g. for precious-metals dental alloys and palladium-based white gold jewellery); as well as substitutes' lower technical performance and higher price.

9 Policy implications

This chapter discusses the policy implications of the evolution of the palladium supply chain's resilience over time. This chapter thus relates to the third and final sub-question: *Given how the four resilience mechanisms have changed over time, what recommendations can be made to policy-makers to promote the palladium supply chain's resilience?*

This chapter consists of three sections. The first section introduces and validates an annual compound resilience index to provide insight into the temporal dynamics of resilience overall. Based on the findings from the previous analyses of the resilience mechanisms, the second section proposes policy recommendations to improve the palladium supply chain's resilience. The third and final section summarises to chapter's findings and addresses the final sub-question.

9.1. Temporal dynamics of resilience overall

Chapters 5, 6, 7, and 8 analysed the evolution over time of the individual indicators of the diversity of supply, price, stockpiling, and substitution mechanisms, respectively. To gain insight into the evolution over time of resilience overall, the indicators from the previous chapters are synthesised into a compound resilience index. Constructing such a compound index can contribute to more informed decision-making and interventions by providing policy-makers with a simplified representation of complex data trends over time (Bulut and Thompson, 2023). Moreover, visualizing the annual compound resilience index scores over time provides insight into the temporal dynamics of the palladium supply chain's resilience, which is the main focus of this study.

9.1.1. Resilience index construction

Constructing a compound resilience index involves two fundamental structural design choices: indicator selection and choosing an appropriate weighting scheme for the indicators. Possible weighting methods include equal weighting, weighting based on experts' domain knowledge, and weighting based on empirical statistical techniques (Bulut and Thompson, 2023). Following Bulut and Thompson (2023), statistical-weighting based on Principal Component Analysis (PCA) is selected as a weighting method. The rationale behind this weighting method is to assign larger weights to indicators that have more explanatory power, i.e. that account for more variance in the dataset of indicators (Bulut and Thompson, 2023).

PCA is a statistical method that creates uncorrelated linear combinations, called principal components, from an original set of indicators in such a way as to preserve as much of the variability from the original set of indicators as possible (Géron, 2022; Jolliffe and Cadima, 2016). The linear combination of the original indicators that explains the maximum amount of variation is called the first principal component (Géron, 2022; Jolliffe and Cadima, 2016). The correlations between the principal components and the original indicators, called component loadings, can be used as weights to construct an index from the original indicators (Broby and Smyth, n.d.; Bulut and Thompson, 2023; Chao and Wu, 2017).

Following Bulut and Thompson (2023), this study uses PCA-based weights to compute the resilience index. The process of computing the resilience index consists of six steps: (i) indicator selection, (ii) indicator scaling, (iii) elimination of redundant indicators, (iv) indicator standardisation, (v) retrieval of indicator weights using PCA, and (vi) index computation (see Figure 9.1) (Bulut and Thompson, 2023; Chao and Wu, 2017).

Figure 9.1: Overview of the process of computing the resilience index. Steps based on Bulut and Thompson (2023 and Savelberg (2022).

In the first step, i.e. indicator selection, the indicators to be included in the resilience index are selected. In Chapter 4, a total of 13 proxy variables were introduced to operationalise the four resilience mechanisms. Eight of these proxy variables are deemed suitable for inclusion in the resilience index[1]: the country-level HHI of PGM reserves, the country-level HHI of primary palladium production, the facility-level HHI of primary palladium production, the company-level HHI of primary palladium production, the EOL-RIR, the country-level HHI of net exports of refined palladium, companionality, and size of total stockpiles in months of demand. For interpretation purposes, it is desirable that higher and lower resilience index scores are associated with higher and lower resilience, respectively. Therefore, six of the eight selected indicators are transformed so that a higher indicator score is associated with higher resilience. This results in the following eight indicators:

1. **Country-level diversity of reserves** = 10,000 – country-level HHI of PGM reserves. Note that country-level diversity of reserves ranges between 0 and 10,000 and is associated with the diversity of supply mechanism.
2. **Country-level diversity of mining** = 10,000 – country-level HHI of primary palladium production. Note that country-level diversity of mining ranges between 0 and 10,000 and is associated with the diversity of supply mechanism.
3. **Facility-level diversity of mining** = 10,000 – facility-level HHI of primary palladium production. Note that facility-level diversity of mining ranges between 0 and 10,000 and is associated with the diversity of supply mechanism.
4. **Company-level diversity of mining** = 10,000 – company-level HHI of primary palladium production. Note that company-level diversity of mining ranges between 0 and 10,000 and is associated with the diversity of supply mechanism.
5. **EOL-RIR**. Note that the EOL-RIR ranges between 0% and 100% and is associated with the diversity of supply mechanism.
6. **Country-level diversity of exports** = 10,000 – country-level HHI of net exports of refined palladium. Note that country-level diversity of exports ranges between 0 and 10,000 and is associated with the diversity of supply mechanism.
7. **Percentage of palladium mined as host metal** = 1 – companionality. Note that the percentage of palladium mined as host metal ranges between 0% and 100% and is associated with the diversity of price mechanism.
8. **Size of total stockpiles in months of demand**. Note that the size of total stockpiles in months of demand can be any positive number and is associated with the stockpiling mechanism.

Based on the data sources identified in Chapter 4 and the indicator computations in Chapters 5, 6, and 7, the longest time series for which all eight indicators above are available is the period 2012-2021. Hence, the resilience index is computed on an annual basis for the years 2012-2021.

In the second step, i.e. indicator scaling, the selected indicators are scaled to ensure they contribute equally to the PCA, regardless of their original scale. Indeed, it is important that all indicators are represented on the same scale before applying PCA (Savelberg, 2022). If the indicators are not scaled to the same range, the variance-maximising PCA algorithm can be more sensitive to the indicators with larger sizes, thereby distorting the results. Hence, following Bulut and Thompson (2023), min-max

[1] Stockpile allocations are considered redundant and not included in the index, because they can be derived from the included stockpile size proxy variable. The (cross) price elasticities are not suitable for inclusion in the index, because they cannot be computed on an annual basis using the identified data sources.

scaling is applied to scale the original indicators to a value between 0 and 1. Min-max scaling entails subtracting the minimum and then dividing by the difference between the maximum and the minimum. The *MinMaxScaler* function from the Python library scikit-learn (Pedregosa et al., 2011) is used.

In the third step, i.e. the elimination of redundant indicators, indicators that have a strong positive correlation are removed to prevent double counting (Chao and Wu, 2017; Savelberg, 2022). Inclusion of highly-correlated indicators is undesirable, because it would lead to double counting and overrepresentation of some resilience mechanisms in the compound resilience index. Therefore, following Savelberg (2022), indicators with a Pearson correlation coefficient larger than 0.7 are removed. Based on the correlation matrix (see Figure F.1 in Appendix F) of the eight indicators, four pairs of indicators are identified that have a correlation exceeding 0.7: the EOL-RIR and the country-level diversity of reserves, the EOL-RIR and the facility-level diversity of mining, the EOL-RIR and the percentage of palladium mined as host metal, and the country-level diversity of reserves and the percentage of palladium mined as host metal. Accordingly, it is decided to remove the EOL-RIR and the country-level diversity of reserves as indicators and compute the index based on the six remaining indicators. Although alternative index compositions are possible, this particular composition of indicators is selected, because it minimises the number of removed indicators, while keeping the only indicator associated with the price mechanism (i.e. the percentage of palladium mined as host metal). The implications of using alternative index compositions are explored in Appendix F.2.

In the fourth step, i.e. the indicator standardisation, the selected scaled indicators are standardised. PCA assumes that the indicators are centred around the origin (i.e. have zero mean) (Géron, 2022). For small datasets it is recommended to use z-score normalisation as a standardisation method (Savelberg, 2022). Z-score normalisation entails subtracting the mean and then dividing by the standard deviation. This transformation scales the data to fit a standard normal distribution with zero mean and unit variance. Hence, in line with Bulut and Thompson (2023), z-score normalisation is applied to the indicators using the *StandardScaler* function from the Python library scikit-learn (Pedregosa et al., 2011).

In the fifth step, the indicator weights are retrieved using PCA. Based on the PCA of the standardised scaled indicators, component loadings are obtained for the first principal component. These component loadings can either be positive or negative and do not necessarily sum up to one. To ensure the weights represent the relative contributions of the original indicators, the component loadings are normalised (Bulut and Thompson, 2023). That is, the absolute values of the component loadings are divided by the total sum of the absolute values of the component loadings. The obtained weights are thus the normalised component loadings for the first principal component (Bulut and Thompson, 2023).

In the sixth and final step, the compound resilience index score is computed by calculating the weighted average of the selected indicators. More specifically, the weighted average is computed by using the scaled non-standardised indicators and the weights obtained from PCA.

The weights obtained for the six selected indicators are shown in Figure 9.2. Recall from Chapter 5 that both the lower and upper bounds were computed for the facility-level and company-level concentrations of primary palladium production. These lower and upper bounds for the production concentrations correspond to upper and lower bounds for the diversity of mining indicators, respectively. The weights in Figure 9.2 are based on using the upper bounds for the facility-level and company-level diversity of mining indicators. The implications of using the lower bounds instead are explored in Appendix F.2.

The PCA-based weights in Figure 9.2 provide insight into the relative importance of the resilience indicators in terms of their contribution to the overall variability in the set of indicators. More specifically, the PCA-based weights indicate the following order of importance of the six indicators (from most to least important): facility-level diversity of mining, percentage palladium mined as host, total stockpile size in months of demand, country-level diversity of exports, company-level diversity of mining, and country-level diversity of mining. Interestingly, these findings suggest that facility-level concentration of mining may be a more informative indicator than country-level concentration of mining, which is typically used in criticality assessments (Schrijvers et al., 2020) and material supply chain resilience studies.

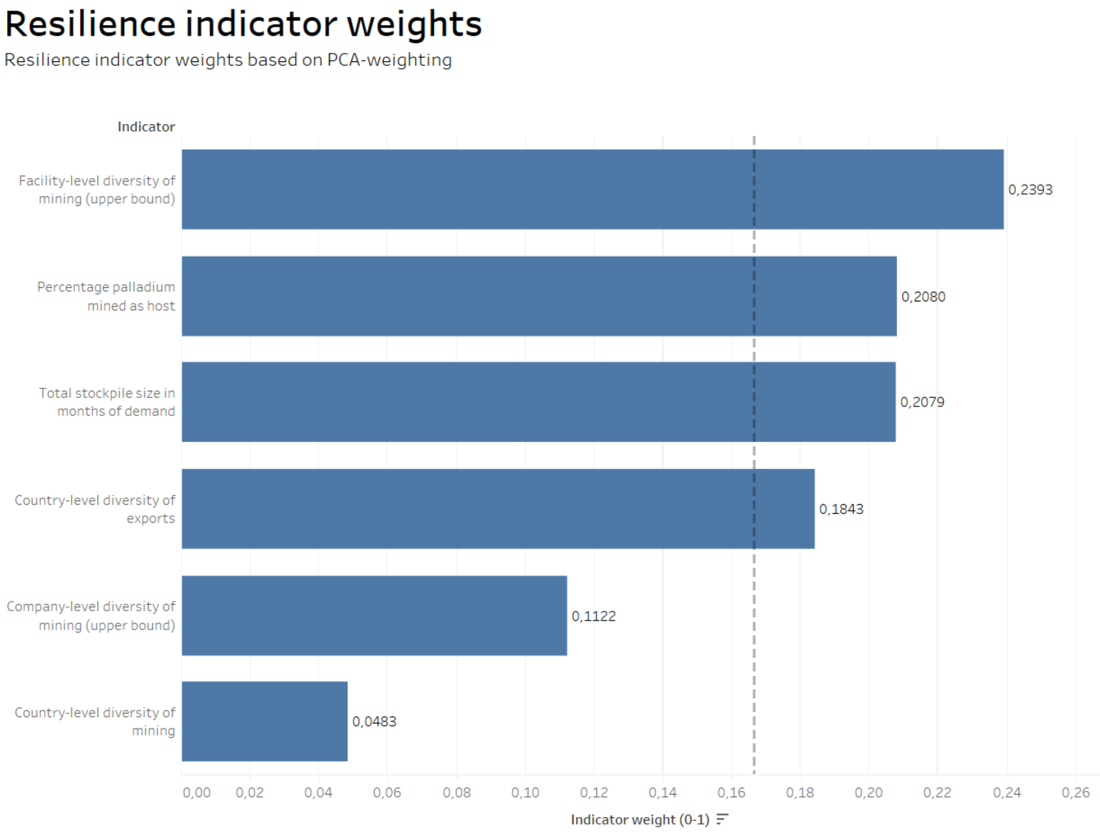

Figure 9.2: Weights associated with the six resilience indicators based on PCA-weighting. The dashed vertical reference line indicates the weights in case of equal weighting (i.e. weights of $\frac{1}{6}$). Note that the indicator weights range between zero and one and sum up to one. The underlying indicator data covers the years 2012-2021.

9.1.2. Temporal analysis of resilience index

Based on the index computation methodology outlined in the previous subsection, the annual resilience index score is computed for the years 2012-2021. Figure 9.3 shows the annual resilience index score as well as the palladium market balance during the years 2012-2021.

It can be noted that an increasing resilience index coincided with a decreasing market deficit during the years 2012-2021. These years were characterised by a structural market deficit (Cowley and Ryan, 2023), indicating a lack of resilience. The market deficit fluctuated over the years, but seems to follow a decreasing trend for the period 2012-2021 overall. This suggests that resilience improved during the period 2012-2021 overall. This is also reflected in the increasing resilience index. The resilience index score fluctuated, but increased by approximately 45.7% from 0.442 to 0.644 during the period 2012-2021 overall. These findings suggest that the palladium supply chain's resilience fluctuated during the years 2012-2021, but improved during the period 2012-2021 overall.

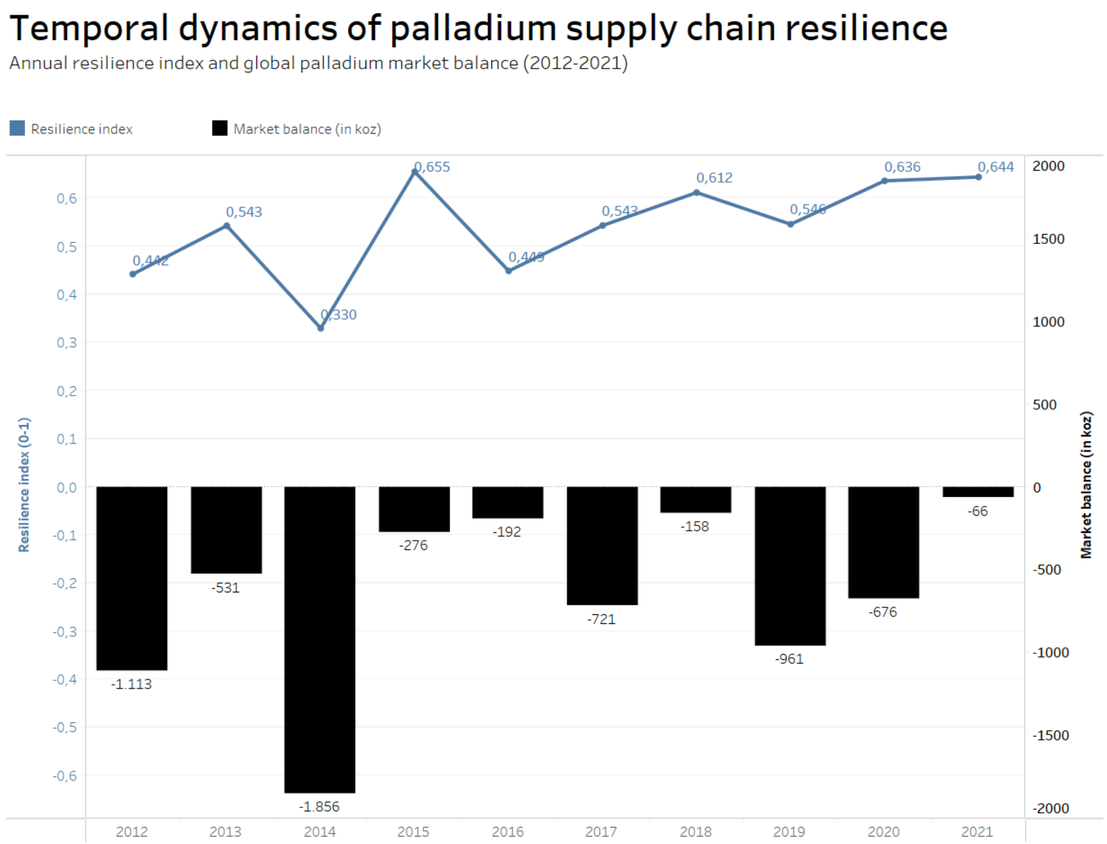

Figure 9.3: Annual resilience index and global palladium market balance (in thousands of troy ounces) during the years 2012-2021. The index score is computed based on PCA-weighting of six indicators: country-level diversity of mining, facility-level diversity of mining (upper bound), company-level diversity of mining (upper bound), country-level diversity of exports, percentage of palladium mined as host metal, and the size of total stockpiles in months of demand. Market balance data is retrieved from Johnson Matthey (2023a).

9.1.3. Resilience index validation

To validate the resilience index introduced in the previous subsections, the relationship between the resilience index and the palladium market balance is explored. The resilience index is considered valid if it is fit for purpose, i.e. if it provides significant insight into the temporal dynamics of the palladium supply chain's resilience. To investigate the validity of the resilience index, its relation to the palladium market balance is investigated, which is considered as an annual performance indicator for resilience.

It is found that there is a relatively strong positive correlation between the resilience index score and the palladium market balance. The Python library Scipy (Virtanen et al., 2020) is used to compute the Spearman and Pearson correlation coefficients between the resilience index and market balance. Spearman's correlation coefficient is approximately 0.62. This indicates a relatively strong positive monotonic relationship between the resilience index and market balance. Pearson's correlation coefficient is approximately 0.75. This indicates a relatively strong positive linear relationship between the resilience index and market balance.

Furthermore, it is found that the resilience index captures the majority of the variability in the market balance. To investigate the relationship between the resilience index and the palladium market balance in more detail, the palladium market balance is regressed on the resilience index for the years 2012-2021. The results of this simple linear regression are shown in Table 9.1. The coefficient estimate of the resilience index indicates that an increase in the resilience index by 0.1 is associated with an increase in the market balance by 389.79 koz, on average. Moreover, note that 56.2% of the variability in the market balance is explained by the regression model.

The findings above suggest that the resilience index is an appropriate indicator for measuring the

Intercept (standard error)	-2758.80*** (667.89)
Resilience index (standard error)	3897.92** (1216.66)
Number of observations	10
R^2	0.562
Uncorrelated residuals (p-value Breusch-Godfrey test)	Yes (0.692)
Homoscedastic residuals (p-value Breusch-Pagan test)	Yes (0.256)
Normal residuals (p-value Shapiro-Wilk test)	Yes (0.154)

Table 9.1: Simple linear regression results of regressing the palladium market balance (in koz) on the resilience index. Note that the 10 observations correspond to the years 2012-2021. Moreover, note that the linear regression assumptions of uncorrelated, homoscedastic, and normal residuals are satisfied.

temporal dynamics of the palladium supply chain's resilience. Moreover, recall that the resilience index is based on quantitative indicators derived from the qualitative Sprecher et al. (2015 resilience framework. More specifically, the underlying indicators of the resilience index relate to the diversity of supply, price, and stockpiling resilience mechanisms identified by Sprecher et al. (2015). Hence, the findings above also suggest that the diversity of supply, price, and stockpiling mechanisms are indeed significantly correlated with resilience, as postulated by Sprecher et al. (2015).

9.2. Policy recommendations

The analysis of the resilience index in the previous section indicated a structural lack of resilience in the last decade, despite an overall improvement of resilience. To further improve the palladium supply chain's resilience, both demand-side and supply-side policy strategies are recommended based on the analyses of the individual resilience mechanism.

It was found that autocatalysts in ICEVs have historically been the largest source of palladium demand, accounting for approximately 85% of global palladium demand in 2022[2]. Hence, policies aimed at reducing the amount of palladium demanded for autocatalysts would be an effective demand-side approach to improve the palladium supply chain's resilience. Accordingly, the following demand-side policy strategies are recommended:

- **Promote further acceleration of the EV transition.** The analysis of the substitution mechanism suggests that policy aimed at material substitution of palladium in autocatalysts is unlikely to be very effective. Despite decades of autocatalyst research, the only effective substitute for palladium is platinum (Nassar, 2015; SFA Oxford, 2017). However, platinum is not a very promising substitute to palladium for three reasons. First, platinum is also a CRM with significant supply risk (European Commission, 2023c). Second, the analysis of palladium's companionality over time indicated that platinum and palladium are often co-mined, implying that platinum supply will likely also be impacted in the event of palladium supply disruptions. Third, it was found that platinum has historically typically been more expensive than palladium, disincentivising substitution. Hence, there are significant limitations to material substitution of palladium in autocatalysts (Nassar, 2015). Accordingly, it was found that price is not a significant driver of palladium catalyst demand in the short term. One important non-price factor driving palladium autocatalyst demand concerns global car sales (WPIC, 2020, 2022). This suggests that a more promising alternative to policy promoting material substitution is EV-promoting policy. EV-promoting policy would incentivise technological substitution of ICEVs by BEVs, which do not require autocatalysts (SFA Oxford, 2019). Policy-makers could for example further accelerate the EV transition by subsidizing EV sales and EV charging infrastructure. A demand-side approach aimed at accelerating the EV transition does come with two major limitations, however. First, although technological substitution of ICEVs by BEVs would reduce the dependence on palladium for mobility, it would likely raise dependence on other CRMs used in BEVs, such as lithium and cobalt. Second, the growth in BEVs is not expected to meaningfully impact palladium demand in the medium term (SFA Oxford, 2019).

[2] Own calculations based on demand data from Johnson Matthey (2023a)

- **Promote shared vehicle use and public transport.** In developed economies, demand for new palladium-containing ICEVs could potentially be reduced by promoting shared vehicle use (e.g. Uber, Lyft, Greenwheels) and public transport (WPIC, 2020).
- **Loosen vehicle emission regulations for ICEVs.** In addition to global car sales, another important non-price factor driving palladium autocatalyst demand concerns vehicle emission regulations. Stricter vehicle emission regulations require higher palladium contents in autocatalysts, thereby raising palladium demand for autocatalysts (WPIC, 2020). In fact, vehicle emission regulations are the biggest drivers of PGM demand and prices (Hughes et al., 2021). Loosening vehicle emission regulations for ICEVs could arguably reduce palladium demand in the short term. Obviously, loosening vehicle emission regulations is undesirable from an environmental perspective, because it would increase pollutant vehicle emissions. This indicates a trade-off between the palladium supply chain's resilience and sustainability in the short term.

On the supply side, the following policy strategies are recommended:

- **Expand strategic stockpiling.** In line with Sprecher et al. (2015), the analysis of the stockpiling mechanism indicated that strategic stockpiles can contribute to resilience by acting as a buffer in case of supply disruptions. However, it was found that total identifiable stockpiles have decreased in recent years, US state stockpiling of palladium has been very limited since 2005, and stockpiling of palladium in the EU is non-existent. Hence, it is recommended to expand strategic stockpiling operations either through centrally-organised state stockpiling or through a public-private stockpiling scheme. However, stockpiling requires significant economic investment. For reference, the acquisition cost for a 60-day EU palladium stockpile is estimated at approximately 733 million Euros (Rietveld et al., 2022).
- **Promote palladium mining outside Russia.** The analysis of the country-level production concentration indicated that primary palladium production has historically been consistently highly concentrated in especially Russia and South Africa. In 2022, Russia, South Africa, Canada, Zimbabwe, the USA, and other countries accounted for approximately 42%, 38%, 7%, 6%, 5%, 1% of primary palladium production, respectively[3]. This suggests that resilience can be improved though diversification of primary production and promoting mining outside Russia and South Africa. It is particularly important to promote mining outside of Russia for four reasons. First, promoting mining outside of Russia could potentially significantly reduce the currently high country-level production concentration. Russia was identified as the largest palladium miner and is therefore the largest contributor to the high primary production concentration. Second, the deteriorating relations between Russia and the West have contributed to an increased supply risk of potential Russian palladium export restrictions in the next few years, making Russian primary supply particularly vulnerable to supply disruptions (Teer and Bertolini, 2022). Third, promoting mining outside of Russia would likely reduce the facility-level production concentration to a low level. The analysis of the facility-level production concentration indicated that production concentration has been low-to-medium in the last decade. It was found that production is fairly diversified in South Africa. In Russia, however, the Kola Division and Polar Division mining facilities combined accounted for all Russian primary production and approximately 40% of global primary production in the last decade. Fourth, promoting mining outside of Russia would significantly reduce the company-level production concentration. The medium-to-high company-level production concentration in the last decade was found to be primarily attributable to the high market share of the Russian mining company Norilsk Nickel. Norilsk Nickel accounted for all Russian primary production and approximately 40% of global primary production in the last decade. To promote palladium mining outside of Russia, the EU could subsidise domestic palladium mining projects, for example in Finland or Poland. Moreover, the EU could reduce red tape for mining projects, e.g. by shortening permitting times.
- **Improve diplomatic (trade) relations with South Africa.** The analysis of the country-level production concentration indicated that South Africa's market share in primary production has significantly increased since the 1960s due to South African production growth exceeding Russian production growth. As a result, South Africa is currently the world's second largest palladium

[3] Own calculations based on production data from the USGS (Schulte, 2023).

miner. Moreover, it was found that global PGM reserves have been consistently highly concentrated during the years 1996-2023 in especially South Africa. In 2023, South Africa, Russia, Zimbabwe, the USA, and Canada accounted for approximately 88.8%, 7.8%, 1.7%, 1.3%, and 0.4% of global PGM reserves[4]. Although Russia has historically been the largest palladium miner, these findings suggests that future primary palladium production is expected to mainly originate from South Africa. Georgitzikis et al. (2023) concur that South Africa together with Zimbabwe and the USA are expected to be the largest contributors to additional primary palladium supply in the coming decade. Hence, it is particularly important for the EU to maintain good diplomatic relations with South Africa to safeguard future supply security.

- **Promote recycling of palladium-containing EOL products, especially electronics.** The analysis of palladium's EOL-RIR and the country-level concentration of trade flows indicated that recycling has significantly contributed to diversification of supply and resilience. The reason for this is that recycling can occur outside the countries in which palladium is geologically concentrated. It was found that palladium recycling has dramatically increased since the 1980s and especially this century. The analysis of palladium's recycling by application indicated that the increase in palladium's secondary supply is primarily attributable to increased recycling of autocatalysts, whose collection and processing efficiency have improved over time. In the long term, however, palladium recycling volumes from autocatalysts are expected to decrease due to the EV transition (Georgitzikis et al., 2023). This implies that future palladium recycling will become more dependent on palladium from EOL electronics. It was found, however, that palladium recycling of EOL electronics has so far remained limited due to insufficient collection infrastructure, the relatively small amounts of palladium in electronics, and the complicated disassembly of EOL electronics. Indeed, collection of EOL electronics is currently insufficient (Van de Camp, 2020; Wittmer et al., 2010) with only around 17.4% of global electronic waste being collected and recycled in 2019 (Tiseo, 2023). Introducing proper payments for consumers' EOL electronics, similar to cars, could potentially improve the collection rate of EOL electronics (Van de Camp, 2020). Furthermore, policy-makers could improve the processing efficiency of EOL electronics by stimulating (or requiring) design for recycling and by subsidising recycling efficiency R&D.

Ultimately, the decision of which policies are considered most desirable depend on policy-makers' prioritisation of competing policy objectives as well as on their risk attitude (Heckmann et al., 2015). Policy-makers have to decide which level of palladium market imbalance is considered acceptable at what environmental and economic cost.

In line with the above, it must be noted that resilience is not necessarily a positive concept (Mancheri et al., 2018; Sprecher et al., 2017). Similar to previous material supply chain resilience studies (Sprecher et al., 2015; Van de Camp, 2020), the policy implications above indicate that supply chain resilience should not be conflated with supply chain sustainability, in environmental or social terms. For example, opening new palladium mines can promote the palladium supply chain's resilience through diversification of supply, but palladium mining is also associated with health and safety issues for mine workers, human rights violations, and environmental pollution (Glaister and Mudd, 2010; Steinweg and de Haan, 2007). Conversely, responsible sourcing initiatives for mined palladium may be desirable from a social and environmental perspective, but "stricter sourcing requirements might have an inhibitory effect on the [⋯] diversity of supply" (Van de Camp, 2020, p. 61).

9.3. Chapter conclusion

This chapter investigated the policy implications of the findings of the temporal analyses of the four resilience mechanisms.

To gain insight into the temporal dynamics of the palladium supply chain's resilience overall, a PCA-based compound resilience index was constructed based on six indicators derived from the previous analyses of the individual resilience mechanisms: country-, company-, and facility-level diversity of mining, country-level diversity of exports, percentage of palladium mined as host metal, and the size of total stockpiles in months of demand. Interestingly, the PCA results suggest that facility-level concentration of mining may be a more informative indicator than the country-level concentration of mining typically used in criticality assessments and material supply chain resilience studies.

[4] Own calculations based on PGM reserves data from the USGS (Schulte, 2023)

Quantitative validation of the resilience index suggests that the resilience index is positively correlated with resilience. It is found that the resilience index has a relatively strong positive correlation with the palladium market balance for the years 2012-2021. Moreover, it is found that the resilience index captures the majority of the variability in the market balance for the period 2012-2021. In terms of quantitative validation of the Sprecher et al. (2015) resilience framework, this implies that the diversity of supply, stockpiling, and price resilience mechanisms do indeed significantly correlate with resilience.

Furthermore, it was found that an increasing resilience index coincided with a decreasing market deficit during the years 2012-2021. These findings indicate an overall improvement of resilience, but nevertheless a structural lack of resilience in the last decade.

Based on the findings from the analyses of the resilience mechanisms, three demand-side and four supply-side policy strategies are recommended to further improve the palladium supply chain's resilience. On the demand side, it is recommended to reduce demand for palladium's dominant application: autocatalysts in ICEVs. Therefore, it is recommended to (i) promote further acceleration of the EV transition, (ii) promote shared vehicle use and public transport, and (iii) loosen vehicle emission regulations for ICEVs. On the supply side, it is recommended to (i) expand strategic stockpiling, (ii) promote palladium mining outside Russia, (iii) improve diplomatic relations with South Africa, and (iv) promote recycling of palladium-containing EOL products, especially, electronics.

10
Discussion

This chapter discusses the relevance and validity of this research's findings. Moreover, this chapter provides suggestions for improvements and recommendations for future research.

10.1. Reflection & suggestions for further research overall

This section discusses this study's contribution to addressing the research gaps in the material criticality and material supply chain resilience literature, as identified in Section 2.8. Moreover, recommendations for further research are proposed.

10.1.1. Temporal dynamics of palladium supply chain resilience

The first research gap identified concerned the fact that, to the best of the author's knowledge, palladium had not been studied from a material supply chain resilience perspective prior to this study. This study investigated the palladium supply chain's resilience by evaluating the four resilience mechanisms identified by Sprecher et al. (2015). This study thus focused explicitly on the palladium supply chain, i.e. the material system part of the overarching product supply chain of palladium-containing final products (see Chapter 3). Consequently, however, the production system of palladium-containing intermediate and final products falls outside the scope of this study. Future research could therefore investigate the resilience of the product supply chain of a palladium-containing product, such as autocatalysts (or ICEVs more broadly). Furthermore, this study explicitly focused on the diversity of supply, price, stockpiling, and substitution mechanisms in the palladium supply chain. However, there are additional mechanisms in the palladium supply chain different from the four considered that can potentially affect resilience. In particular, improving material properties can be identified as a resilience mechanism distinct from the substitution mechanism that can promote resilience by lowering material demand (Sprecher et al.,2015, 2017). Indeed, 'thrifting' (i.e. using less of a material) can provide a suitable alternative to substitution to reduce palladium demand for autocatalysts (IPA, 2024). Expansion of the conceptual framework used with additional mechanisms would result in a more complete view of the palladium supply chain's resilience. However, it would also make the framework more complex to investigate, interpret, and compare across different material supply chains.

This study's analysis of material supply chain resilience differed from previous follow-up studies to the Sprecher et al. (2015) framework in two major ways. First, more research was needed to investigate the temporal dynamics of material supply chain resilience (Van den Brink et al., 2020). Second, these previous studies mostly used qualitative methods (i.e. interviews and literature review) rather than quantitative methods to evaluate the resilience mechanisms. This study, by contrast, used quantitative indicators to evaluate how the palladium supply chain's resilience and the underlying resilience mechanisms changed over time.

10.1.2. Quantitative validation of the Sprecher et al. (2015) framework

Another research gap identified in the literature was a lack of quantitative validation of the Sprecher et al. (2015) resilience framework. As a first step towards quantitative validation of this qualitative framework, this study operationalised the four resilience mechanisms in terms of quantitative indicators (see

Chapter 4). Moreover, this study combined a selection of the indicators associated with the diversity of supply, price, and stockpiling mechanisms into a compound resilience index (see Chapter 9). It was found that this resilience index has a relatively strong positive correlation with the palladium market balance and accounts for the majority of the variability in the market balance. In line with the Sprecher et al. (2015) resilience framework, this suggests that the diversity of supply, price, and stockpiling mechanisms combined are indeed significantly correlated with resilience.

This study provides a good starting point for quantitative validation of the Sprecher et al. (2015) resilience framework. Nevertheless, several improvements to this study's approach can be made to quantitatively validate the framework in a more rigorous manner:

Firstly, further research could consider time lags in the quantitative validation of the resilience index. This study did not consider time lags in its quantification of the correlation between the resilience index and market balance. Time-lagged cross correlation could be used to investigate to what extent the resilience index provides insight into future changes in the market balance.

Secondly, future research could operationalise the substitution mechanism in terms of indicators that can be included in the compound resilience index. This resilience index in its current form does not include indicators associated with the substitution mechanism. This study does operationalise the substitution mechanism in terms of quantitative proxy variables: the (cross) price elasticities of demand. However, these proxy variables are computed based on multi-year data and are therefore not suitable for computing an annual resilience index. In hindsight, it would have been better to account for such considerations in the initial operationalisation of the resilience mechanisms in Chapter 4.

Thirdly, to quantitatively validate the resilience mechanisms individually, future research could investigate the correlation between the indicators associated with each mechanism and the market balance more extensively. This study investigated the impact of the stockpiling mechanism on resilience by providing a visual analysis of the annual impact of total identifiable stockpile allocations on the market balance (see Chapter 5). Moreover, this study investigated the impact of the price and substitution mechanisms on the market balance by estimating the price elasticities of supply and demand, respectively, using regression modelling (see Chapters 6 and 8). Further research could use regression modelling to also quantify the correlation between the country-level HHI, and EOL-RIR and the market balance, for which relatively long time-series data was identified. For the remaining resilience mechanism indicators, however, quantitative validation was found to be challenging, because two major data limitations complicate statistical time-series modelling.

- The time-series data available for the selected indicators is typically short. For example, the facility-level HHI, company-level HHI, and size of total stockpiles were only identified for 10, 13, and 11 years (i.e. data points), respectively. To enable time-series modelling for these indicators, further research could collect data for additional years to extend the time series. However, this study found that the data availability of the underlying mine-level production and revenue data was limited. Indeed, there is poor availability of mining data on a sub-national level of granularity (Jasansky et al., 2023). Moreover, where data was available, the manual collection process was found to be extremely time-consuming (see Appendix A). Hence, future research could use data mining techniques, including large language models, to automate the data collection process from sources such as JOGMEC Global Mining Trends reports and mining company reports.
- The data for several of the selected indicators was found to be quite static over time. For example, the country-level concentration of PGM reserves and palladium's companionality were found to be constant for several years. Future research could use alternative, more dynamic indicators to operationalise these resilience mechanisms that are more suitable for quantitative validation. However, finding alternative resilience mechanism indicators is challenging due to the limited data availability often encountered when investigating CRMs (Jasansky et al., 2023; Schrijvers et al., 2020; Sprecher, Daigo, et al., 2017; Wagner et al., 2019). For palladium specifically, finding relevant data is further complicated by the fact that data sources often do not differentiate between the individual PGMs (Schrijvers et al., 2020).

10.1.3. Relative importance of resilience indicators

Review of the existent literature also indicated that more research was needed to investigate the relative informativeness of the indicators used in criticality assessments in terms of criticality and resilience.

The PCA conducted in this study provided some insight into the relative contribution of the resilience mechanism indicators. In terms of the relative contribution to the overall variability of the set of identified indicators, the following order of importance of the indicators was found (from most to least important): facility-level diversity of mining, percentage palladium mined as host, total stockpile size in months of demand, country-level diversity of exports, company-level diversity of mining, and country-level diversity of mining. This suggests that the facility-level concentration of mining may be a more informative indicator than the country-level concentration of mining, which is typically used in criticality assessments (Schrijvers et al., 2020).

Additionally, it would be useful to assess the relative contribution of the resilience indicators in terms of their predictive power with respect to the market balance. Future research could therefore use statistical feature importance techniques to also provide insight into the relative correlation of the resilience mechanism indicators with the market balance.

10.1.4. Further investigate impact EV transition on palladium supply chain

In addition to the suggestions for further research outlined above, it is recommended to further investigate the implications of the EV transition on the palladium supply chain's resilience. The EV transition will undoubtedly have a significant impact on the palladium supply chain (SFA Oxford, 2023d). More research is needed to investigate how palladium supply and demand will be impacted by different EV-policy and BEV-demand scenarios. This study's analysis of the palladium supply chain illustrated that the palladium supply chain is a complex adaptive system that involves many different actors and is characterised by feedbacks and delays (e.g. between price changes and supply changes). Hence, future research could use simulation approaches such as agent-based modelling and exploratory system dynamics modelling (e.g., see Kwakkel and Pruyt, 2015) to investigate the palladium supply chain under different EV-transition scenarios. Several of the metrics computed in this study, such as companionality and the (cross) price elasticities, can potentially serve as inputs for such models.

10.2. Reflection & suggestions for further research per resilience mechanism

This section reflects on the scientific contribution and limitations of this study's analysis of the individual resilience mechanisms. Moreover, suggestions for further research per resilience mechanism are proposed.

10.2.1. Diversity of supply mechanism

Existent material criticality assessments and previous material supply chain resilience studies were found to have under-explored the concentration of reserves (Rietveld et al., 2022), the facility-level production concentration, and concentration of trade flows. This study, by contrast, quantitatively evaluated these factors by computing the country-level HHI of PGM reserves, facility-level HHI of refined palladium production, and country-level HHI of refined palladium trade flows indicators over time.

Future research could improve on this study's analysis of the diversity of supply mechanism in at least two ways.

Firstly, future research could investigate the contribution of artisanal and small-scale mining to the palladium supply chain's diversity of supply. In addition to the primary and secondary supply investigated in this study, ASM can also contribute to diversity of supply (Sprecher et al., 2015). Palladium's association with ASM has been identified as 'low' (Material Insights, 2023), which suggests that ASM is relatively rare for palladium. Still, future research could investigate to what extent ASM occurs for palladium and how this affects the palladium supply chain's resilience.

Secondly, the availability and quality of data relating to diversity of supply requires improvement:

- Available estimates of PGM reserves are highly uncertain and require quality improvement. Indeed, for CRMs more generally, the data availability and quality of resource and reserves estimates require improvement (Bastein and Rietveld, 2015). This study found that PGM reserves estimates available in the literature are not consistent. Reducing the uncertainty in PGM reserves estimates would enable more accurate analysis of the concentration of reserves and, therefore, future production concentration.
- Data regarding CRM production capacity utilisation is currently not readily available (Bastein and Rietveld, 2015). Following previous criticality assessments and material supply chain resilience

studies (Schrijvers et al., 2020; Silberglitt et al., 2013; Van den Brink et al., 2022), this study evaluated production concentration by computing the HHI based on material production volumes. In addition to actual production volumes, it would also be useful to explore production capacity data. Indeed, capacity utilisation (or free capacity) would be an useful indicator for supply vulnerability and production flexibility (Bastein and Rietveld, 2015). Production capacity utilisation data could provide insight into the extent to which producers (i.e. mines, companies, countries) can compensate for supply disruptions at other producers and contribute to resilience.

- Palladium production volumes are currently not available for the intermediate stages of primary production. The primary palladium production volumes used in this study referred to refined palladium derived from mining. No distinction could be made between the various palladium processing stages (mining, concentration, smelting, refining). The reason for this is that mining companies only report production volumes of refined palladium per mine (European Commission, 2023c; JRC, 2023b). Reporting of production volumes for the intermediate processing stages could prove insight into the diversity of supply per processing stage rather than for primary production overall.
- Data regarding trade flows of PGM ores and concentrates specifically is currently not available. This study did not analyse trade flows of PGM ores and concentrates, because international trade statistics do not provide sufficient detail to separate trade flows of PGM ores and concentrates from trade flows of other precious metals (Georgitzikis et al., 2023; JRC, 2023b). More specifically, UN Comtrade could further sub-divide the 'precious metal ores and concentrates' (HS261690) trade flow category to distinguish between PGM ores and concentrates and the ores and concentrates of other precious metals. Quality improvement of this trade flow data would enable analysis of the concentration of palladium trade flows on the level of ores and concentrates.
- Data regarding trade flows of refined palladium requires quality improvement. This study's analysis of refined palladium trade flows was limited by the fact that export data for major producers Russia and South Africa was missing for the majority of the years considered. It was found that UN Comtrade export data of 'palladium, unwrought or in powder form' (HS711021) does not cover Russian and/or South African exports in approximately 66% of the years between 1988-2022. A partial explanation for this is that Russian PGM production and sales data were difficult to obtain prior to 2006, because they were confidential under Russian law (George, 2005). Quality improvement of refined palladium trade flow data would enable a more accurate analysis of the temporal dynamics of the concentration of refined palladium trade flows.

10.2.2. Price mechanism

To the best of the author's knowledge, this study was the first to compute how palladium's companionality has changed over time. It was found that palladium evolved from by-product, to co-product, to host metal in recent years. This finding challenges the dominant view in the literature of palladium as a by-product (e.g., see DeCarlo and Goodman, 2022; SFA Oxford, 2023d). Moreover, previous material supply chain resilience studies did not provide a rigorous quantification of the effect of the first economic feedback loop, but used the Pearson correlation coefficient (Van den Brink et al., 2022) or qualitative methods. This study, by contrast, used regression to estimate the price elasticity of primary supply, which provides more detailed quantitative information about how price changes affect primary supply.

Future research could further investigate the price mechanism in at least three ways.

Firstly, the temporal dynamics of palladium's companionality can be investigated for additional years. This study computed palladium's companionality for the years 2010-2021. The reason for selecting this time period is that the required revenue contributions by metal for Norlilsk Nickel's mines are not readily available for earlier years. Since Norislk Nickel's mines account for around 40% of global primary palladium production, it will likely be challenging to compute the companionality prior to 2010 in a manner that accurately reflects the global situation.

Secondly, further research could investigate the temporal dynamics of palladium's companionality using alternative definitions of host and companion metals. Following Nassar et al. (2015), this study defined a host metal as the metal with the highest contribution to the mine's revenue and defined the remaining metals as companions. Alternatively, a host metal could be defined as a metal whose revenue contribution covers the mine's operational costs and is therefore financially independent of other metals for its recovery (Nassar et al., 2015). Further research could provide insight into the implications of using such alternative definitions on the temporal dynamics of palladium's companionality.

Thirdly, the regression analyses of the (cross) price elasticities of supply could be improved by accounting for the non-normality of the residual errors. Several of the regression results did not pass the Shapiro-Wilk test, indicating non-normal residual errors. The non-normality of residual errors in the regression results is not surprising considering the small sample size (a maximum of 43 observations for the years 1980-2022). The computation of prediction intervals requires normally distributed residuals (Greene, 2012). Hence, the regression models presented in Chapter 6 are suitable for inference, but less suitable for prediction. Further research could account for the non-normality of the residual errors by collecting longer time-series data and/or using statistical techniques, such as bootstrapping.

10.2.3. Stockpiling mechanism

To investigate the stockpiling mechanism, previous material supply chain resilience studies used solely qualitative methods to analyse state stockpiling in particular (e.g., see Galimberti, 2021; Mancheri et al., 2018; Sprecher et al., 2015; Van den Brink et al., 2022). This study, by contrast, provided a temporal analysis of the quantitative indicators of stockpile size and identifiable allocations. Moreover, this study explicitly distinguished between state, company, and investor stockpiling.

The analysis of the stockpiling mechanism was limited by the poor availability and reliability of palladium stockpiling data, with the exception of publicly-disclosed ETF stockpiles. In particular, Russian state palladium stockpiles seem to have had a significant impact of the palladium market historically, but are generally not publicly disclosed due to their status as a state secret (Kitco News, 2010). This opacity in stockpile reporting obscures the overall impact of palladium stockpiling on resilience.

10.2.4. Substitution mechanism

Material criticality assessments and previous material supply chain resilience studies have primarily relied on qualitative methods, i.e. expert interviews and literature review, to evaluate substitution (Achzet and Helbig, 2013; Helbig et al., 2016). This study, by contrast, used regression to estimate the price elasticity of demand per palladium application to gain insight into the extent to which price changes have historically incentivised substitution.

Further research could extend this study's analysis of the substitution mechanism in at least two ways.

Firstly, future research could investigate the (cross) price elasticities of demand using different time lags for the price variables. This study considered multiple time lags for the regression analyses of the (cross) price elasticities of supply, but not for the (cross) price elasticities of demand. That is, only the immediate (i.e. within the same year) effects of price changes on demand were modelled. However, the effect (feedback loop) of price changes on demand through substitution is characterised by delays, as producers need time to adapt product design and production processes (Sprecher et al., 2015; Van den Brink et al., 2022). Modelling different time lags for the price variables could provide insight into the duration of the delay associated with substitution. Therefore, modelling different time lags would also provide insight into the rapidity with which the palladium supply chain can recover from a disruption.

Secondly, as stated in the previous section, future research could use alternative quantitative indicators to operationalise the substitution mechanism that are suitable for index inclusion. This would enable the inclusion of substitution-related indicators in the resilience index developed in this study. For example, the suitability of alternative materials for palladium substitution could be quantified using the multi-attribute vector distance (MAVD). The MAVD quantifies the aggregated difference across a set of the most important attributes between the material of interest and a potential substitute (Nassar, 2015).

11 Conclusion

This study investigated the temporal dynamics of palladium's supply chain resilience. More specifically, the aim of this thesis was to address the research question: *How has the palladium supply chain's resilience changed over time, and what challenges or opportunities does this imply for policy-makers?* To that end, the palladium supply chain was conceptualised as a system consisting of the four interlinked resilience mechanisms identified by Sprecher et al. (2015): the diversity of supply, price, stockpiling, and substitution mechanisms. In contrast to the mostly qualitative methods used in previous follow-up studies to the Sprecher et al. (2015) resilience framework, this study operationalised the resilience mechanisms in terms of quantitative indicators

The diversity of supply mechanism was operationalised by considering four indicators: the concentration of reserves, the concentration of primary production, recycling's contribution to meeting demand, and the concentration of trade flows. It was found that PGM reserves have historically been consistently highly concentrated in especially Russia and South Africa, which accounted for approximately 96-99% of global PGM reserves in the years 1996-2023. Although the country-level primary production concentration and Russian dominance have significantly decreased since the 1960s, primary production remains highly concentrated on a country level. During the last decade, the overall facility-level and company-level primary production concentrations have been low-to-medium and medium-to-high, respectively, and did not display a clear trend over time. Primary production from Russia has been particularly problematic historically, with only two Norilsk Nickel-owned mines accounting for all Russian primary production and around 40% of global primary production. These findings suggest that global palladium mine production has historically been particularly vulnerable to supply disruptions in Russia and South Africa. Moreover, it was found that recycling volumes, the share of secondary supply in total supply, and the EOL-RIR have significantly increased since the 1980s, primarily driven by increased recycling of autocatalysts. It was also found that trade flows of refined palladium, which originate from both mining and recycling, are much more diversified than palladium mine production. These findings indicate that increased recycling has contributed to resilience by diversifying supply away from the countries in which it is geologically concentrated. However, the fact that the EOL-RIR has historically remained lower than the recycling rate indicated that increased recycling has not been able to keep up with palladium's faster growing demand.

The price mechanism was operationalised by considering three indicators: the price elasticity of supply, the cross price elasticity of supply, and companionality. Regression analysis of the price elasticity of secondary supply indicated that the palladium price has not significantly affected secondary palladium supply within a period of 10 years. By contrast, regression analysis of the price elasticities of primary and overall supply indicated that palladium price increases have historically raised primary and overall supply, but only slightly and after a delay of at least 6 years. The inelasticity of primary palladium supply can be explained by investors' reluctance to invest in new primary palladium supply due to the uncertain palladium price and demand outlook. Moreover, regression analysis of the cross price elasticities indicated that price increases of palladium's host metals (platinum, nickel, copper) have historically raised primary and overall supply more than palladium price increases, but still only slightly and after a delay of at least 6 years. The stronger supply-raising effect of palladium's host metal prices can be explained by the finding that palladium has almost exclusively been mined as a companion to nickel, platinum, and copper up until 2016. The dominant view in the literature of palladium as a by-product, however, has become outdated. It was found that palladium evolved from by-product, to co-product, to host metal due to palladium price increases in the period 2010-2021. This could imply that palladium's primary and overall supply have become more responsive to the palladium price in recent years. Overall, it can be concluded that the price mechanism has historically contributed to resilience by raising palladium supply, but only slightly and after a time delay of at least 6 years. This suggests that the price mechanism can arguably not significantly contribute to resilience during fast disruptions due to the time delay associated with expanding primary supply.

The stockpiling mechanism was operationalised by considering two indicators: the time palladium stockpiles can satisfy societal palladium demand when regular supply sources are disrupted and stockpile allocations. It was found that the lack of transparency regarding palladium stockpiling is problematic from a resilience perspective, because it enables stockpiling actors to manipulate the palladium market. Relatedly, it was found that the opaque nature of palladium stockpiling negatively affected long-term resilience by hindering proper functioning of the price mechanism. A trade-off was identified between the short-term positive impact of stockpile sales and the self-correcting ability of the system to expand supply in response to higher prices. Furthermore, it was found that palladium stockpiling has historically both positively and negatively affected resilience, depending on the strategy and position of the stockpiling actor. It was also found that total palladium stockpiles significantly declined during the years 2012-2022 due to Russian state and ETF palladium stockpile sales incentivised by the high palladium price. This decline reduced the buffering capacity of the stockpiling mechanism in case of future temporary supply disruptions, but simultaneously contributed to resilience by mitigating the structural market deficit.

The substitution mechanism was operationalised by considering two indicators: the price elasticity of demand and the cross price elasticity of demand. Regression analysis of the price elasticities of palladium demand by application indicated that substitution has historically not significantly affected autocatalyst, chemical, and overall palladium demand in the short term (i.e. within one year). Moreover, it was found that substitution has historically only slightly reduced palladium demand for dental and biomedical, electrical, jewellery, and other applications in the short term. Accordingly, regression analysis of the cross price elasticities indicated that palladium's potential substitutes (platinum, nickel, gold, and silver) have historically mostly acted as complements rather than substitutes in the short term. Overall, it can be concluded that the substitution mechanism has historically not provided much resilience to fast disruptions. After all, it was found that substitution has historically not significantly reduced overall palladium demand in the short term. Possibly, palladium demand is more elastic and the substitution mechanism's effect on resilience is more positive in the longer term. However, the brief reviews of substitutes by palladium application suggest that the inelasticity of palladium demand likely also results from a lack of suitable substitutes. Platinum was identified as the only suitable substitute for palladium's dominant application, i.e. autocatalysts. Substitution of palladium was found to be limited by co-mining of substitutes with palladium; Japanese government subsidies for palladium-based dental alloys; subjective consumer preference; as well as substitutes' lower technical performance and higher price.

To gain insight into the temporal dynamics of resilience overall, a PCA-weighted compound resilience index was computed based on six indicators from the diversity of supply, price, and stockpiling mechanisms. Interestingly, the PCA results suggested that facility-level concentration of mining may be a more informative indicator than the country-level concentration of mining typically used in criticality assessments and material supply chain resilience studies.

Quantitative validation of the resilience index suggested that the resilience index is positively correlated with resilience. The resilience index has a relatively strong positive correlation with the palladium market balance and captures the majority of the variability in the market balance for the period 2012-2021. In terms of quantitative validation of the Sprecher et al. (2015) resilience framework, this implies that the diversity of supply, stockpiling, and price resilience mechanisms do indeed significantly correlate with resilience.

Furthermore, it was found that an increasing resilience index coincided with a decreasing market deficit during the years 2012-2021. These findings indicate an overall improvement of resilience, but nevertheless a structural lack of resilience in the last decade.

To further improve the palladium supply chain's resilience, three demand-side and four supply-side policy strategies are recommended. On the demand-side, it is recommended to (i) promote further acceleration of the EV transition, (ii) promote shared vehicle use and public transport, and (iii) loosen vehicle emission regulations for ICEVs. On the supply-side, it is recommended to (i) expand strategic stockpiling, (ii) promote palladium mining outside Russia, (iii) improve diplomatic relations with South Africa, and (iv) promote recycling of palladium-containing EOL products, especially electronics.

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A

Appendix: Data retrieval and preparation

The data source files and data analysis files mentioned in the sections below are made publicly available at https://drive.google.com/drive/folders/1wCprTfJGjo6QvgZBjBKBoIyDDmMUJCPG?usp=sharing.

A.1. Supply and demand data: Johnson Matthey dataset

The original dataset by Johnson Matthey (2023a)[1] covers the years 1980-2023 and includes primary supply by region, secondary supply by application, and demand by region and application. Three modifications are made to the original dataset:

- Data for the year 2023 is not considered in this study, because this year is ongoing at the time of writing.
- For the years 2000-2022, the original JM-dataset distinguishes between Russian state stockpile sales and Russian primary supply. However, this study includes the Russian state stockpile sales in the Russian primary supply for two reasons. First, prior to the year 2000, the JM-dataset does not distinguish between Russian primary supply and Russian state stockpile sales, therefore, for consistency this distinction is also not made after 2000. Second, primary supply reported by JM includes not only underlying mine production, but also sales from producer stockpiles (Cowley and Ryan, 2023). Arguably, the Russian state stockpile sales can be considered as producer stockpile sales, because the Russian palladium stockpiles were created in the Soviet Union of the 1970s and 1980s, when the mining company Norilsk Nickel was still a state-owned company (Kitco News, 2010; Norilsk Nickel, 2023b; Risk and Policy Analysts Ltd., 2012).
- The file layout of the original JM-dataset is modified to enable loading the data into Python. More specifically, the original data is manually copied into a new excel file[2].

The data preparation tasks described above are performed using Excel and result in a modified version of the JM-dataset[3].

After making the adjustments above, several supply and demand totals are calculated. More specifically, total primary supply is calculated by summing the primary supply of the reported regions. Moreover, secondary supply is computed by summing the secondary supply of the reported application categories. Furthermore, total supply is computed by summing primary supply and secondary supply. Total demand is computed by summing the demand of the reported application categories. Finally, the market balance is computed as total supply minus total demand. Eventually, these final data preparation tasks result in the same total primary supply, total secondary supply, total demand, and market

[1] See *Johnson_Matthey_supply_demand_original.xlsx*

[2] See *Johnson_Matthey_supply_demand_modified_format.xlsx*

[3] See *JM_supply_demand_cleaned.xlsx*

balance figures as reported in the original JM-dataset. The data preparation tasks described above are performed using Python[4] and result in an excel file of cleaned supply and demand data[5].

In terms of data exploration, it can be noted that several negative demand values are present in the JM-dataset. These negative values are valid and can be explained by changes in stockpiles and pre-consumer recycling (Cowley and Ryan, 2023). In particular, the negative investment demand figures indicate sales from investor (ETF) stockpiles, which effectively contribute to supply. Another example of a negative demand value is European demand for the chemical sector in 2014. This negative value indicates a situation in which palladium obtained from pre-consumer recycling and stockpile use exceeds demand. In such a situation, a user (e.g. chemical company) can decide to sell a part or all of its excess palladium.

A.2. Price data

This study uses price data for palladium and several other metals (platinum, nickel, etc.). Price data for these metals, with the exception of palladium, is retrieved from the World Bank (2023b). More specifically, these concern nominal annual prices. Since the identified World Bank dataset does not include palladium prices, palladium price data is obtained differently. Nominal daily palladium prices (in USD/troy oz) for the years 1977-2023 are retrieved from Macrotrends (2023)[6]. To obtain the nominal annual palladium price, the average of the daily prices in a given year is computed. In order to compare price developments over time, the nominal metal prices are adjusted for inflation using the Commodity Price Index from the World Bank (2023b)[7]. More specifically, for a given year t, the nominal annual price is converted into the real annual price of year t in constant 2022 US dollars using the following formula: Real price for year t in 2022 US dollars = Nominal price for year $t * \frac{CPI_{2022}}{CPI_t}$. These data preparation tasks are performed using Python[8] and result in an excel file of cleaned price data[9].

A.3. Mining data

In order to investigate the diversity of supply mechanism, primary production data on both country-level and facility-level are retrieved. The following subsections discuss the preparation of the country-level and facility-level production data in more detail.

A.3.1. Country-level production data

Previous material supply chain resilience studies have typically retrieved country-level production data from the USGS and BGS (e.g., Van den Brink et al., 2022). However, this study primarily retrieves the country-level production data from the German Mineral Resources Agency (DERA, 2020). The reason for this is that DERA integrates data from a wide variety of sources, including the USGS and BGS, and also covers earlier years. Hence, palladium primary production (i.e. mine production) during the years 1964-2019 is manually retrieved from DERA's Raw Materials Information System (ROSYS)[10]. Since DERA (2020) currently does not cover the post-2019 years, primary production data for the years 2020-2022 is manually retrieved from the USGS PGM Mineral Commodity Summaries (Schulte, 2022, 2023). Since the country-level production data is manually retrieved from DERA ROSYS and USGS reports, it is stored in an excel file[11] to allow for further processing.

A.3.2. Facility-level production data

Production data per mine is retrieved from Buchholz et al. (2022, see supplementary information), company reports, and JOGMEC Global Mining Trends reports. For the year 2018, Buchholz et al. (2022) identified 20 palladium mines and reported their production, which in total covered 87.4% of global primary production in that year. This dataset was used as a starting point. Compared to Buchholz et al. (2022), this study does not differentiate between the Sudbury Operations and Raglan mines in

[4] See *preprocess_JM_supply_demand_data.ipynb*
[5] See *JM_supply_demand_cleaned.xlsx*
[6] See *macrotrends_palladium_price_1977_2023.csv*
[7] See *worlbank_commodity_price_data.xls*
[8] See *preprocess_price_data.ipynb*)
[9] See *cleaned_price_data.xlsx*
[10] Unfortunately the ROSYS wesbite does not offer a data export function.
[11] See *country_level_mine_production_1964_2022.xlsx*

Canada, since only the combined production volume of these mines was identified for years other than 2018 (see, Glencore, 2016, 2017, 2019).

Since this study focuses on how production concentration evolves over time, additional data sources were identified to retrieve production per mine for years other than 2018. JOGMEC publishes Global Mining Trends reports per country annually, which identify a list of mines and their production per raw material. Unfortunately, the process of retrieving data from these reports is extremely time-consuming for two reasons. First, these reports are only available in Japanese[12]. Second, these reports typically only cover a single country, single year, and multiple materials, therefore, a large number of documents needs to be interpreted carefully to obtain palladium production per mine over time.

In addition to JOGMEC, production data per mine was retrieved from company reports published by the parent companies of the identified mines, including African Rainbow Minerals, Anglo American Platinum, Impala Platinum, Glencore, Norilsk Nickel, and Zimplats. Retrieving production data per mine from these reports is time-consuming, because these reports are typically over a hundred pages long.

Since manually retrieving the production data per mine was found to be extremely time-consuming, production data per mine is only retrieved for the years 2012-2021 and primarily for mines in the countries Russia and South Africa. The rationale behind selecting the years 2012-2021 is that these most recent years are deemed to best reflect the current mine-level production concentration. The reason for primarily focusing on mines in Russia and South Africa is that the country-level production data indicated that Russia and South Africa have historically been the largest palladium producers, implying that the mines in these countries account for most of the global palladium production.

- The identified palladium mines are mines for which a palladium production volume was found for at least one year during the period 2012-2021. Mines which are known to produce palladium, but for which no palladium production volume was found in the identified data sources, are not included in the list of mines. Hence, the list of identified palladium mines is non-exhaustive.
- To obtain the amount that most accurately represents the palladium production of a specific mine, production from third party feed is excluded (if reported) and only amounts are used which are explicitly linked to only palladium[13]. Hence, if only a mine's total PGM production or combined platinum-palladium production is reported[14], these amounts are not included in this study's analysis.
- The assumption is made that production volumes reported in oz refer to troy ounce (i.e. 31.10 g) rather than avoirdupois ounce (i.e. 28.35 g). Norilsk Nickel (2022, p. 319) and Zimplats (2019, p. 184) make explicit that palladium amounts are reported in troy ounces. However, other data sources do not always explicitly state that the amount in oz reported concerns troy ounce (e.g. the JOGMEC reports). However, precious metals are typically measured in troy ounces (LBMA, 2017, slide 18). Therefore, unless specified otherwise by the data source, it is assumed that the amount reported in oz refers to troy ounces.
- Amounts reported in tonnes (t) are converted to troy ounces by multiplying the amount by 32150.7474.

Since the production data per mine is manually retrieved from reports, it is stored in an excel file[15] to allow for further processing.

A.4. Stockpiling data

In this study, the stockpiling mechanism is investigated by considering the size of stockpiles and stockpile allocations. To that end, data is retrieved both relating to the size of stockpiles and stockpile allocations for various stockpiling actors.

Stockpile size data is manually retrieved from Bloomberg, Reuters, and the USGS. More specifically, estimates of the size of total palladium ETF stockpiles and total palladium stockpiles for the years 2010-2019 are retrieved from Mazneva and Pakiam (2020). Estimates of the size of total palladium stockpiles for the years 2022-2023 are retrieved from Hobson and Harvey (2023). Since this data is

[12]The author cannot interpret Japanese without using a translation tool. Fortunately, the names of the mining sites are reported in English.

[13]In the JOGMEC reports, only production volumes corresponding to パラジウム (palladium in Japanese) are retrieved.

[14]For example, only combined production is reported for the Rustenburg and Marikana mines in JOGMEC (2023c).

[15]See *production_per_mine.xlsx*

manually retrieved from websites, it is stored in an excel file[16] to enable further data processing. Data regarding the amount of palladium held in the US National Defense Stockpile is retrieved for the years 1995-2018 from several USGS PGM minerals yearbooks (2004, 2005, 1999b, 2014b, 2015b, 2016, 2017, 2018). Since this data is manually retrieved from USGS reports, it is stored in an excel file[17] to allow for further processing.

Stockpile allocation data is manually retrieved from Johnson Matthey, Reuters, and SFA Oxford. Following O'Connell et al. (2015), this study distinguishes between five types of stockpile allocations. First, Russian state stockpile allocations. Russian state stockpile sales (in koz) are retrieved for the years 2005-2013 and 2014-2019 from Johnson Matthey (2023a) and Alexander et al. (2019), respectively. Second, investor stockpile allocations. Total investor stockpile allocations for the years 1998-2022 are retrieved from Johnson Matthey (2023a). Moreover, a particular type of investor stockpile allocations, ETF stockpile allocations, are retrieved for the years 2007 and 2008-2022 from O'Connell et al. (2015) and several SFA Oxford Palladium Standard reports (2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023d), respectively. Third, industry stockpile allocations are retrieved for the years 2005-2009 and 2010-2019 from O'Connell et al. (2015) and Alexander et al. (2019), respectively. Fourth, stockpile allocations by Stillwater mining company are retrieved for the years 2005-2009 and 2010-2019 from O'Connell et al. (2015) and Alexander et al. (2019), respectively. Finally, US National Defense Stockpile allocations are retrieved for the years 2005-2014 from O'Connell et al. (2015). Since the stockpile allocation data is manually retrieved from several reports, it is stored in an excel file[18] to enable further data processing.

In terms of data preparation, the stockpile size data and stockpile allocation data are merged into a single file. Moreover, total stockpile allocation for the years 1998-2022 are computed by summing over the five types of stockpile allocations. These data preparation tasks are performed using Python[19] and result in an excel file of cleaned stockpiling data[20].

[16] See *total_stockpile_size_estimates.xlsx*
[17] See *USGS_NDS_palladium_stockpile_size.xlsx*
[18] See *stockpile_allocations_1998_2022.xlsx*
[19] See *preprocess_stockpiling_data.ipynb*
[20] See *stockpiling_data_cleaned.xlsx*

B

Appendix: The diversity of supply mechanism

B.1. Facility-level concentration of primary production

The calculations related to the facility-level concentration are based on a selection of the world's palladium mines. Table B.1 shows an overview of the number of identified mine production volumes and their coverage of global palladium mine production for the years 2012-2021.

Year	Number of identified mine production volumes	Share of global primary production covered (%)
2012	26	85.2
2013	28	84.9
2014	25	79.7
2015	19	70.4
2016	22	76.8
2017	20	74.2
2018	22	88.4
2019	16	72.5
2020	22	74.5
2021	23	75.2

Table B.1: Overview of identified palladium mine production volumes for the years 2012-2021. Global primary production is based on country-level production data from DERA (2020) and the USGS (2022, 2023) for the years 2012-2019 and 2020-2021, respectively.

B.2. Map of Bushveld Complex

Figure B.1 shows a map of PGM mines located in the Bushveld Complex in South Africa.

B.3. Maps of Norilsk Nickel mining facilities

Figures B.2 and B.3 show maps of the Kola Division and Polar division, respectively. Note that both mines and processing facilities are owned by Norilsk Nickel and located in close proximity of each other, indicating vertical integration.

B.4. PGM recycling facilities in the EU

Figure B.4 provides a non-exhaustive overview of PGM mining and processing facilities in the EU. It can be noted that the number of mines is very small, but that there are several processing facilities, particularly of secondary feedstock (i.e. recycling) (Georgitzikis et al., 2023).

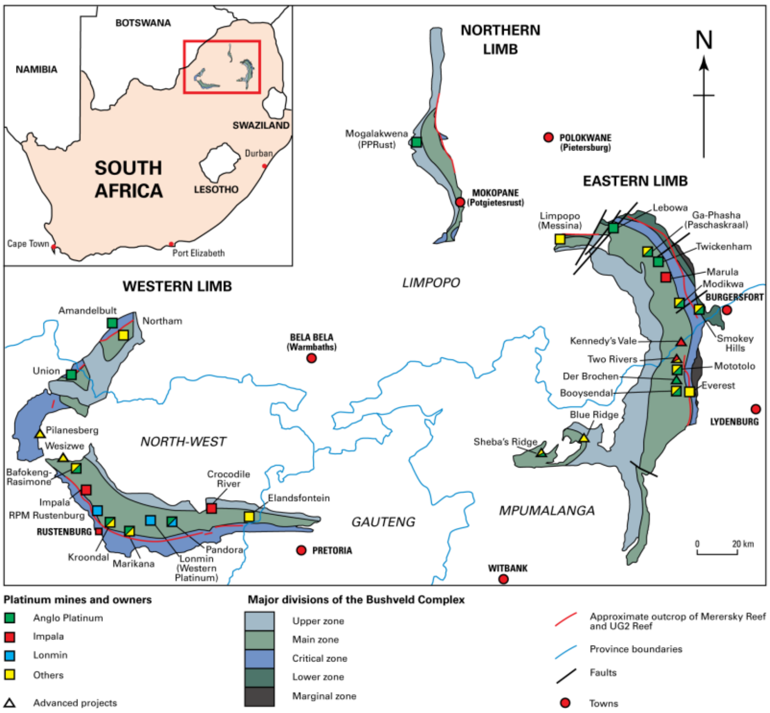

Figure B.1: Map of PGM mines located in the Bushveld Complex in South Africa. Figure adopted from Gunn and Benham (2009, p. 5).

Figure B.2: Map of the Kola Division in Russia, i.e. a mining facility of Norilsk Nickel, in 2015. For geographical reference, the yellow dots indicate Russian towns. Figure adopted from Norilsk Nickel (2016, p. 16).

Figure B.3: Map of the Polar Division in Russia, i.e. a mining facility of Norilsk Nickel, in 2015. For geographical reference, the yellow dots indicate Russian towns. Figure adopted from Norilsk Nickel (2016, p. 14).

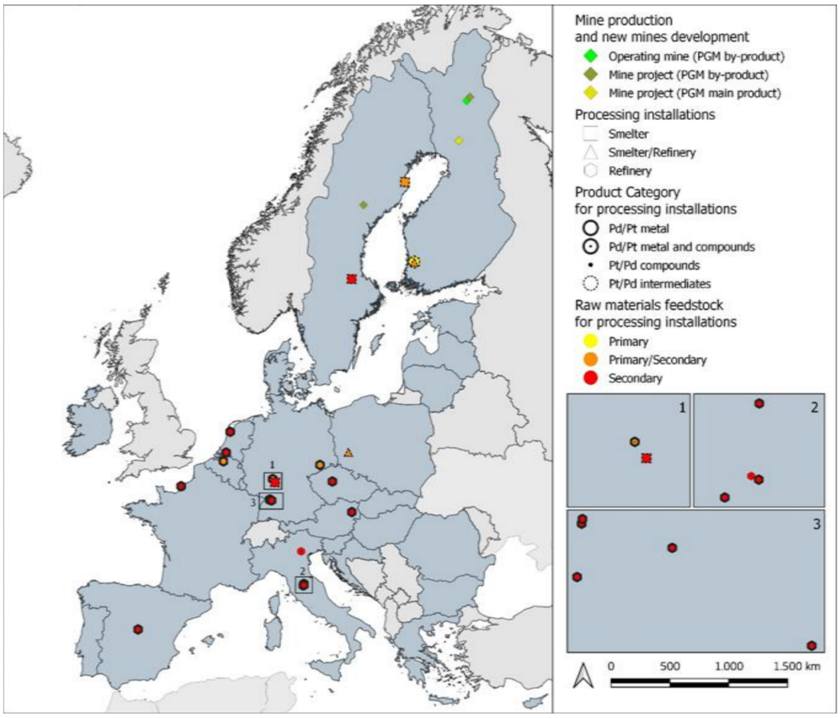

Figure B.4: Non-exhaustive overview of PGM mines and processing facilities in the EU. Figure adopted from Georgitzikis et al. (2023, p. 6).

C

Appendix: The price mechanism

C.1. Companionality

The calculations related to companionality are based on a selection of the world's palladium mines. Table C.1 shows how much of global primary palladium production for the years 2010-2021 is covered by the selected mines.

Year	Share of global primary production covered (%)
2010	56
2011	51
2012	55
2013	66
2014	69
2015	63
2016	64
2017	66
2018	67
2019	71
2020	68
2021	70

Table C.1: Annual percentage of global primary palladium production covered by the selection of mines for the years 2010-2021. Global primary production is based on country-level production data from DERA (2020) and the USGS (2022, 2023) for the years 2010-2019 and 2020-2021, respectively.

C.2. Regression results: primary supply

To estimate the (cross) price elasticities of primary supply, five explanatory variables are considered: logged primary supply in the previous year, logged time-lagged real palladium price, logged time-lagged real platinum price, logged time-lagged real nickel price, and logged time-lagged real copper price. Accordingly, for each time lag of 0-10 years, 30[1] possible models of the five explanatory variables are explored.

For each time lag of 0-5 years, those regression models that have significant coefficients for all explanatory variables are shown in Figures C.1, C.2, C.3, C.4, C.5, and C.6, respectively. Note that these statistically significant regression results do not pass the Breusch-Godfrey and/or Breusch-Pagan tests at a 5% significance level. This implies that the residual errors of these models are auto-correlated

[1]There are 32 (i.e. 2^5) possible combinations of five explanatory variables. The combination with no explanatory variables and the combination with only the logged total primary supply in the previous year as explanatory variable are not considered, because they do not provide insight into (cross) price elasticities.

and/or heteroscedastic, rendering these models unreliable. Accordingly, it is reported in Chapter 6 that no reliable and statistically significant results are obtained for time lags of 0-5 years.

	1	2	3	4	5	6	7	8
Number of observations	43	43	43	43	43	43	43	43
R^2	0.371	0.375	0.319	0.347	0.504	0.522	0.454	0.418
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.000)	False (0.000)	False (0.000)	False (0.001)	False (0.000)	False (0.000)	False (0.000)
Breusch-Pagan passed? (p-value)	False (0.034)	True (0.953)	True (0.070)	True (0.060)	True (0.078)	False (0.005)	True (0.712)	True (0.089)
Shapiro-Wilk passed? (p-value)	True (0.403)	False (0.015)	False (0.011)	True (0.366)	True (0.258)	True (0.507)	True (0.204)	True (0.089)
Condition number	54	176	250	182	237	297	232	279
Intercept	6.565*** (0.415)	2.613** (1.207)	2.818** (1.317)	3.656*** (1.058)	3.164*** (1.101)	2.816** (1.118)	4.277*** (1.004)	2.233* (1.199)
ln_palladium_price_in_2022_USD_per_oz	0.315*** (0.064)	-	-	-	0.212*** (0.066)	0.246*** (0.060)	0.208*** (0.074)	-
ln_platinum_price_in_2022_USD_per_oz	-	0.827*** (0.167)	-	-	0.562*** (0.171)	-	-	0.527** (0.239)
ln_nickel_price_in_2022_USD_per_metric_tonne	-	-	0.582*** (0.133)	-	-	0.423*** (0.119)	-	-
ln_copper_price_in_2022_USD_per_metric_tonne	-	-	-	0.561*** (0.120)	-	-	0.338** (0.137)	0.29* (0.168)
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-	-

Figure C.1: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using non-lagged prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7
Number of observations	42	42	42	42	42	42	42
R^2	0.325	0.418	0.325	0.357	0.486	0.495	0.434
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.000)	False (0.000)	False (0.000)	False (0.001)	False (0.000)	False (0.000)
Breusch-Pagan passed? (p-value)	False (0.018)	True (0.713)	False (0.038)	True (0.070)	True (0.072)	False (0.003)	True (0.704)
Shapiro-Wilk passed? (p-value)	False (0.025)	False (0.037)	False (0.002)	True (0.739)	True (0.276)	True (0.224)	True (0.401)
Condition number	54	177	248	181	242	295	229
Intercept	6.765*** (0.423)	2.505** (1.140)	3.054** (1.266)	3.833*** (1.015)	3.095*** (1.115)	2.974** (1.109)	4.295*** (0.985)
ln_palladium_price_in_2022_USD_per_oz_lag1	0.288*** (0.066)	-	-	-	0.157** (0.069)	0.219*** (0.061)	0.171** (0.074)
ln_platinum_price_in_2022_USD_per_oz_lag1	-	0.844*** (0.157)	-	-	0.624*** (0.179)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag1	-	-	0.56*** (0.128)	-	-	0.427*** (0.118)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag1	-	-	-	0.543*** (0.115)	-	-	0.366*** (0.134)
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-

Figure C.2: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 1 year for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

For each time lag of 6-10 years, those regression models that are reliable (i.e. pass the Breusch-Godfrey and Breusch-Pagan tests) and have significant coefficients for all explanatory variables are shown in Figures C.7, C.8, C.9, C.10, and C.11, respectively. Note that reliable and statistically significant price elasticities of primary palladium supply are found for each of the time lags of 6-10 years. Moreover, note that reliable and statistically significant cross price elasticities of primary palladium supply with respect to nickel are found for each of the time lags of 6-10 years. Lastly, note that reliable and statistically significant cross price elasticities of primary palladium supply with respect to copper are found only for the time lags of 9-10 years.

	1	2	3	4	5	6	7
Number of observations	41	41	41	41	41	41	41
R^2	0.288	0.374	0.3	0.336	0.429	0.452	0.407
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.001)	False (0.001)	False (0.000)	False (0.002)	False (0.003)	False (0.001)
Breusch-Pagan passed? (p-value)	False (0.020)	True (0.968)	True (0.132)	False (0.026)	True (0.109)	False (0.030)	True (0.421)
Shapiro-Wilk passed? (p-value)	True (0.160)	True (0.127)	False (0.030)	True (0.614)	True (0.677)	True (0.608)	True (0.305)
Condition number	57	175	246	184	239	292	229
Intercept	6.876*** (0.444)	3.111*** (1.143)	3.52*** (1.251)	4.069*** (1.026)	3.615*** (1.137)	3.326*** (1.123)	4.375*** (0.993)
ln_palladium_price_in_2022_USD_per_oz_lag2	0.275*** (0.069)	-	-	-	0.145* (0.076)	0.21*** (0.065)	0.162** (0.076)
ln_platinum_price_in_2022_USD_per_oz_lag2	-	0.763*** (0.158)	-	-	0.566*** (0.185)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag2	-	-	0.516*** (0.126)	-	-	0.4*** (0.119)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag2	-	-	-	0.519*** (0.117)	-	-	0.367*** (0.133)
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-

Figure C.3: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 2 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7
Number of observations	40	40	40	40	40	40	40
R^2	0.32	0.365	0.319	0.345	0.44	0.502	0.445
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.002)	False (0.002)	False (0.000)	False (0.003)	False (0.008)	False (0.001)
Breusch-Pagan passed? (p-value)	False (0.014)	True (0.911)	True (0.215)	False (0.016)	True (0.093)	False (0.040)	True (0.429)
Shapiro-Wilk passed? (p-value)	True (0.056)	False (0.040)	True (0.078)	True (0.417)	True (0.208)	True (0.112)	True (0.331)
Condition number	61	174	244	187	235	291	230
Intercept	6.718*** (0.458)	3.437*** (1.115)	3.611*** (1.194)	4.143*** (1.008)	3.915*** (1.083)	3.177*** (1.041)	4.286*** (0.942)
ln_palladium_price_in_2022_USD_per_oz_lag3	0.306*** (0.072)	-	-	-	0.179** (0.080)	0.24*** (0.065)	0.197** (0.076)
ln_platinum_price_in_2022_USD_per_oz_lag3	-	0.721*** (0.154)	-	-	0.499*** (0.178)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag3	-	-	0.509*** (0.121)	-	-	0.399*** (0.109)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag3	-	-	-	0.514*** (0.115)	-	-	0.356*** (0.123)
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-

Figure C.4: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 3 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7	8
Number of observations	39	39	39	39	39	39	39	39
R^2	0.356	0.362	0.358	0.351	0.449	0.561	0.48	0.423
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.001)	False (0.001)	False (0.000)	False (0.002)	False (0.006)	False (0.001)	False (0.001)
Breusch-Pagan passed? (p-value)	False (0.001)	True (0.907)	True (0.146)	False (0.009)	False (0.050)	False (0.012)	True (0.630)	True (0.287)
Shapiro-Wilk passed? (p-value)	True (0.083)	True (0.050)	True (0.090)	True (0.370)	True (0.469)	True (0.293)	True (0.172)	True (0.157)
Condition number	64	172	241	186	233	288	229	318
Intercept	6.643*** (0.450)	3.818*** (1.060)	3.674*** (1.101)	4.36*** (0.964)	4.343*** (1.022)	3.152*** (0.932)	4.38*** (0.875)	2.878** (1.129)
ln_palladium_price_in_2022_USD_per_oz_lag4	0.323*** (0.071)	-	-	-	0.2** (0.083)	0.253*** (0.062)	0.22*** (0.074)	-
ln_platinum_price_in_2022_USD_per_oz_lag4	-	0.671*** (0.147)	-	-	0.425** (0.172)	-	-	0.4* (0.198)
ln_nickel_price_in_2022_USD_per_metric_tonne_lag4	-	-	0.505*** (0.111)	-	-	0.397*** (0.097)	-	0.293* (0.150)
ln_copper_price_in_2022_USD_per_metric_tonne_lag4	-	-	-	0.492*** (0.110)	-	-	0.332*** (0.113)	-
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-	-

Figure C.5: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 4 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7	8
Number of observations	38	38	38	38	38	38	38	38
R^2	0.377	0.349	0.378	0.358	0.447	0.588	0.507	0.428
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.002)	False (0.003)	False (0.001)	False (0.003)	False (0.023)	False (0.004)	False (0.003)
Breusch-Pagan passed? (p-value)	False (0.006)	True (0.604)	True (0.342)	False (0.004)	True (0.159)	False (0.047)	True (0.688)	True (0.675)
Shapiro-Wilk passed? (p-value)	True (0.683)	True (0.140)	True (0.305)	True (0.490)	True (0.925)	True (0.923)	True (0.217)	True (0.383)
Condition number	65	170	238	186	230	284	229	314
Intercept	6.64*** (0.440)	4.163*** (1.030)	3.814*** (1.042)	4.502*** (0.935)	4.749*** (0.991)	3.298*** (0.869)	4.424*** (0.831)	3.151*** (1.081)
ln_palladium_price_in_2022_USD_per_oz_lag5	0.328*** (0.070)	-	-	-	0.214** (0.086)	0.255*** (0.060)	0.231*** (0.071)	-
ln_platinum_price_in_2022_USD_per_oz_lag5	-	0.626*** (0.143)	-	-	0.36** (0.171)	-	-	0.333* (0.190)
ln_nickel_price_in_2022_USD_per_metric_tonne_lag5	-	-	0.492*** (0.105)	-	-	0.384*** (0.091)	-	0.316** (0.143)
ln_copper_price_in_2022_USD_per_metric_tonne_lag5	-	-	-	0.479*** (0.107)	-	-	0.323*** (0.106)	-
ln_total_primary_supply_in_koz_lag1	-	-	-	-	-	-	-	-

Figure C.6: Statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 5 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	42	37
R^2	0.923	0.627
Breusch-Godfrey passed? (p-value)	True (0.961)	True (0.052)
Breusch-Pagan passed? (p-value)	True (0.356)	True (0.154)
Shapiro-Wilk passed? (p-value)	True (0.343)	True (0.667)
Condition number	181	280
Intercept	0.76** (0.359)	3.511*** (0.775)
ln_total_primary_supply_in_koz_lag1	0.914*** (0.042)	-
ln_palladium_price_in_2022_USD_per_oz_lag6	-	0.246*** (0.057)
ln_platinum_price_in_2022_USD_per_oz_lag6	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag6	-	0.37*** (0.082)
ln_copper_price_in_2022_USD_per_metric_tonne_lag6	-	-

Figure C.7: Reliable and statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 6 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3
Number of observations	42	36	36
R^2	0.923	0.648	0.87
Breusch-Godfrey passed? (p-value)	True (0.961)	True (0.165)	True (0.898)
Breusch-Pagan passed? (p-value)	True (0.356)	True (0.119)	True (0.447)
Shapiro-Wilk passed? (p-value)	True (0.343)	True (0.617)	True (0.117)
Condition number	181	276	378
Intercept	0.76** (0.359)	3.696*** (0.705)	1.058* (0.521)
ln_total_primary_supply_in_koz_lag1	0.914*** (0.042)	-	0.759*** (0.076)
ln_palladium_price_in_2022_USD_per_oz_lag7	-	0.213*** (0.053)	-
ln_platinum_price_in_2022_USD_per_oz_lag7	-	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag7	-	0.375*** (0.075)	0.107* (0.056)
ln_copper_price_in_2022_USD_per_metric_tonne_lag7	-	-	-

Figure C.8: Reliable and statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 7 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	42	35
R^2	0.923	0.637
Breusch-Godfrey passed? (p-value)	True (0.961)	True (0.080)
Breusch-Pagan passed? (p-value)	True (0.356)	True (0.207)
Shapiro-Wilk passed? (p-value)	True (0.343)	True (0.552)
Condition number	181	272
Intercept	0.76** (0.359)	3.995*** (0.672)
ln_total_primary_supply_in_koz_lag1	0.914*** (0.042)	-
ln_palladium_price_in_2022_USD_per_oz_lag8	-	0.178*** (0.053)
ln_platinum_price_in_2022_USD_per_oz_lag8	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag8	-	0.369*** (0.071)
ln_copper_price_in_2022_USD_per_metric_tonne_lag8	-	-

Figure C.9: Reliable and statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 8 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4
Number of observations	34	42	34	34
R^2	0.471	0.923	0.578	0.56
Breusch-Godfrey passed? (p-value)	True (0.054)	True (0.961)	True (0.187)	True (0.085)
Breusch-Pagan passed? (p-value)	True (0.157)	True (0.356)	True (0.472)	True (0.789)
Shapiro-Wilk passed? (p-value)	True (0.908)	True (0.343)	True (0.575)	True (0.154)
Condition number	226	181	268	231
Intercept	4.843*** (0.736)	0.76** (0.359)	4.572*** (0.674)	4.856*** (0.649)
ln_nickel_price_in_2022_USD_per_metric_tonne_lag9	0.396*** (0.074)	-	0.329*** (0.071)	-
ln_palladium_price_in_2022_USD_per_oz_lag9	-	-	0.152*** (0.054)	0.154*** (0.055)
ln_platinum_price_in_2022_USD_per_oz_lag9	-	-	-	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag9	-	-	-	0.341*** (0.078)
ln_total_primary_supply_in_koz_lag1	-	0.914*** (0.042)	-	-

Figure C.10: Reliable and statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 9 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3
Number of observations	42	33	33
R^2	0.923	0.464	0.478
Breusch-Godfrey passed? (p-value)	True (0.961)	True (0.051)	True (0.066)
Breusch-Pagan passed? (p-value)	True (0.356)	True (0.127)	True (0.288)
Shapiro-Wilk passed? (p-value)	True (0.343)	True (0.947)	True (0.667)
Condition number	181	264	231
Intercept	0.76** (0.359)	5.492*** (0.683)	5.55*** (0.645)
ln_total_primary_supply_in_koz_lag1	0.914*** (0.042)	-	-
ln_palladium_price_in_2022_USD_per_oz_lag10	-	0.128** (0.056)	0.133** (0.055)
ln_platinum_price_in_2022_USD_per_oz_lag10	-	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag10	-	0.253*** (0.073)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag10	-	-	0.279*** (0.077)

Figure C.11: Reliable and statistically significant regression results for estimating the (cross) price elasticities of primary supply using a time lag of 10 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_primary_supply_in_koz_lag_1* refers to the primary supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

C.3. Regression results: secondary supply

To estimate the price elasticities of secondary palladium supply, two explanatory variables are considered: logged time-lagged real palladium price and logged total primary supply in the previous year. Accordingly, for each time lag of 0-10 years, two models are explored: a model that has the logged time-lagged palladium price as the only explanatory variable (model 1) and a model that has both the logged time-lagged palladium price and the logged secondary supply in the previous year as explanatory variables (model 2). For each time lag of 0-10 years, the regression results of these two models are shown in Figures C.12, C.13, C.14, C.15, C.16, C.17, C.18, C.19, C.20, C.21, C.22. Note that 9 regression results in total have statistically significant coefficients for all explanatory variables, but do not pass the Breusch-Godfrey test at a 5% significance level. This implies that these regression results have auto-correlated residual errors, rendering these results unreliable. The remaining 11 regression results contain statistically insignificant coefficients. Accordingly, it is reported in Chapter 6 that no reliable and statistically significant results are obtained for time lags of 0-10 years.

	1	2
Number of observations	39	38
R^2	0.429	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.476)
Breusch-Pagan passed? (p-value)	True (0.290)	True (0.059)
Shapiro-Wilk passed? (p-value)	False (0.033)	False (0.027)
Condition number	60	88
Intercept	-3.328* (1.801)	0.593*** (0.208)
ln_palladium_price_in_2022_USD_per_oz	1.443*** (0.274)	-0.052^ (0.040)
ln_total_secondary_supply_in_koz_lag1	-	0.98*** (0.018)

Figure C.12: Regression results for estimating the price elasticity of secondary palladium supply using no time lag for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz* refers to the logged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	39	38
R^2	0.423	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.456)
Breusch-Pagan passed? (p-value)	True (0.265)	True (0.409)
Shapiro-Wilk passed? (p-value)	False (0.007)	False (0.012)
Condition number	60	87
Intercept	-3.244* (1.808)	0.482** (0.210)
ln_palladium_price_in_2022_USD_per_oz_lag1	1.442*** (0.277)	-0.029^ (0.040)
ln_total_secondary_supply_in_koz_lag1	-	0.973*** (0.018)

Figure C.13: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 1 year for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag1* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	39	38
R^2	0.442	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.425)
Breusch-Pagan passed? (p-value)	True (0.716)	True (0.570)
Shapiro-Wilk passed? (p-value)	False (0.005)	False (0.009)
Condition number	58	90
Intercept	-3.374* (1.762)	0.488** (0.219)
ln_palladium_price_in_2022_USD_per_oz_lag2	1.482*** (0.273)	-0.03^ (0.042)
ln_total_secondary_supply_in_koz_lag1	-	0.973*** (0.018)

Figure C.14: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 2 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag2* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	39	38
R^2	0.477	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.448)
Breusch-Pagan passed? (p-value)	True (0.871)	True (0.965)
Shapiro-Wilk passed? (p-value)	False (0.038)	False (0.005)
Condition number	61	93
Intercept	-4.268** (1.797)	0.274^ (0.230)
ln_palladium_price_in_2022_USD_per_oz_lag3	1.643*** (0.283)	0.015^ (0.045)
ln_total_secondary_supply_in_koz_lag1	-	0.961*** (0.019)

Figure C.15: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 3 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag3* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	39	38
R^2	0.476	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.472)
Breusch-Pagan passed? (p-value)	True (0.945)	True (0.330)
Shapiro-Wilk passed? (p-value)	True (0.239)	True (0.053)
Condition number	64	96
Intercept	-4.821** (1.897)	-0.003^ (0.228)
ln_palladium_price_in_2022_USD_per_oz_lag4	1.745*** (0.301)	0.075^ (0.046)
ln_total_secondary_supply_in_koz_lag1	-	0.944*** (0.018)

Figure C.16: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 4 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag4* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

C.4. Regression results: overall supply

To estimate the (cross) price elasticities of overall palladium supply, five explanatory variables are considered: logged total primary supply in the previous year, logged time-lagged real palladium price, logged time-lagged real platinum price, logged time-lagged real nickel price, and logged time-lagged real copper price. Accordingly, for each time lag of 0-10 years, 30 possible models of the five explanatory variables are explored. For each time lag of 0-5 years, those regression models that have signifi-

	1	2
Number of observations	38	38
R^2	0.475	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.567)
Breusch-Pagan passed? (p-value)	True (0.871)	True (0.129)
Shapiro-Wilk passed? (p-value)	True (0.084)	True (0.085)
Condition number	65	98
Intercept	-4.543** (1.889)	-0.019^ (0.234)
ln_palladium_price_in_2022_USD_per_oz_lag5	1.721*** (0.301)	0.079^ (0.047)
ln_total_secondary_supply_in_koz_lag1	-	0.944*** (0.018)

Figure C.17: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 5 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag5* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	37	37
R^2	0.48	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.710)
Breusch-Pagan passed? (p-value)	True (0.725)	True (0.597)
Shapiro-Wilk passed? (p-value)	True (0.107)	False (0.016)
Condition number	66	100
Intercept	-4.421** (1.889)	-0.135^ (0.235)
ln_palladium_price_in_2022_USD_per_oz_lag6	1.722*** (0.303)	0.096* (0.048)
ln_total_secondary_supply_in_koz_lag1	-	0.945*** (0.019)

Figure C.18: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 6 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag6* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	36	36
R^2	0.486	0.993
Breusch-Godfrey passed? (p-value)	False (0.000)	True (0.679)
Breusch-Pagan passed? (p-value)	True (0.705)	True (0.127)
Shapiro-Wilk passed? (p-value)	True (0.068)	False (0.029)
Condition number	66	101
Intercept	-4.235** (1.872)	-0.156^ (0.242)
ln_palladium_price_in_2022_USD_per_oz_lag7	1.71*** (0.301)	0.098* (0.050)
ln_total_secondary_supply_in_koz_lag1	-	0.947*** (0.020)

Figure C.19: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 7 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag7* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

cant coefficients for all explanatory variables are shown in Figures C.23, C.24, C.25, C.26, C.27, and C.28, respectively. Note that these statistically significant regression results do not pass the Breusch-Godfrey and/or Breusch-Pagan tests at a 5% significance level. This implies that the residual errors of these models are auto-correlated and/or heteroscedastic, rendering these models unreliable. Accordingly, it is reported in Chapter 6 that no reliable and statistically significant results are obtained for time lags of 0-5 years.

	1	2
Number of observations	35	35
R^2	0.47	0.991
Breusch-Godfrey passed? (p-value)	False (0.001)	True (0.520)
Breusch-Pagan passed? (p-value)	True (0.887)	True (0.647)
Shapiro-Wilk passed? (p-value)	True (0.079)	False (0.006)
Condition number	67	103
Intercept	-3.895** (1.912)	0.154^ (0.267)
ln_palladium_price_in_2022_USD_per_oz_lag8	1.673*** (0.309)	0.028^ (0.055)
ln_total_secondary_supply_in_koz_lag1	-	0.967*** (0.022)

Figure C.20: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 8 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag8* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	34	34
R^2	0.456	0.991
Breusch-Godfrey passed? (p-value)	False (0.001)	True (0.583)
Breusch-Pagan passed? (p-value)	True (0.942)	True (0.881)
Shapiro-Wilk passed? (p-value)	True (0.137)	False (0.003)
Condition number	67	103
Intercept	-3.507* (1.937)	0.131^ (0.272)
ln_palladium_price_in_2022_USD_per_oz_lag9	1.627*** (0.314)	0.028^ (0.056)
ln_total_secondary_supply_in_koz_lag1	-	0.97*** (0.023)

Figure C.21: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 9 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag9* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	33	33
R^2	0.456	0.99
Breusch-Godfrey passed? (p-value)	False (0.001)	True (0.734)
Breusch-Pagan passed? (p-value)	True (0.784)	True (0.692)
Shapiro-Wilk passed? (p-value)	True (0.069)	False (0.007)
Condition number	67	102
Intercept	-3.185^ (1.917)	-0.005^ (0.271)
ln_palladium_price_in_2022_USD_per_oz_lag10	1.59*** (0.312)	0.065^ (0.056)
ln_total_secondary_supply_in_koz_lag1	-	0.957*** (0.023)

Figure C.22: Regression results for estimating the price elasticity of secondary palladium supply using a time lag of 10 years for the palladium price. The coefficient estimates for the explanatory variables are displayed on the bottom 3 rows. The explanatory variable *ln_paladium_price_in_2022_USD_per_oz_lag10* refers to the logged time-lagged palladium price (in 2022 US dollars/oz). The explanatory variable *ln_total_supply_in_koz_lag_1* refers to secondary palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and ^,*,**, and *** indicate no, 10%, 5%, and 1% significance, respectively.

For each time lag of 6-10 years, those regression models that are reliable (i.e. pass the Breusch-Godfrey and Breusch-Pagan tests) and have significant coefficients for all explanatory variables are shown in Figures C.29, C.30, C.31, C.32, and C.33, respectively. Note that reliable and statistically significant price elasticities of overall palladium supply are found for each of the time lags of 6-10 years. Moreover, note that reliable and statistically significant cross price elasticities of overall palladium supply with respect to nickel are found for each of the time lags of 6-10 years. Lastly, note that reliable and

	1	2	3
Number of observations	43	43	43
R^2	0.511	0.626	0.624
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.005)	False (0.000)
Breusch-Pagan passed? (p-value)	False (0.034)	False (0.029)	True (0.112)
Shapiro-Wilk passed? (p-value)	True (0.448)	True (0.118)	True (0.876)
Condition number	54	237	232
Intercept	5.835*** (0.444)	2.008* (1.164)	2.603** (1.014)
ln_palladium_price_in_2022_USD_per_oz	0.45*** (0.069)	0.334*** (0.069)	0.299*** (0.075)
ln_platinum_price_in_2022_USD_per_oz	-	0.633*** (0.181)	-
ln_nickel_price_in_2022_USD_per_metric_tonne	-	-	-
ln_copper_price_in_2022_USD_per_metric_tonne	-	-	0.477*** (0.138)
ln_total_supply_in_koz_lag1	-	-	-

Figure C.23: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using non-lagged prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3
Number of observations	42	42	42
R^2	0.462	0.492	0.606
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.000)	False (0.000)
Breusch-Pagan passed? (p-value)	False (0.048)	True (0.413)	True (0.334)
Shapiro-Wilk passed? (p-value)	True (0.136)	True (0.391)	True (0.943)
Condition number	54	181	229
Intercept	6.063*** (0.461)	1.898* (1.102)	2.588** (1.004)
ln_palladium_price_in_2022_USD_per_oz_lag1	0.42*** (0.072)	-	0.255*** (0.076)
ln_platinum_price_in_2022_USD_per_oz_lag1	-	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag1	-	-	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag1	-	0.779*** (0.125)	0.515*** (0.137)
ln_total_supply_in_koz_lag1	-	-	-

Figure C.24: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 1 year for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

statistically significant cross price elasticities of overall palladium supply with respect to platinum and copper are found only for the time lags of 7-10 years.

	1	2	3	4	5
Number of observations	41	41	41	41	41
R^2	0.414	0.286	0.467	0.543	0.574
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.000)	False (0.000)	False (0.004)	False (0.002)
Breusch-Pagan passed? (p-value)	True (0.086)	True (0.089)	True (0.232)	False (0.030)	True (0.520)
Shapiro-Wilk passed? (p-value)	True (0.150)	False (0.005)	True (0.489)	True (0.217)	True (0.446)
Condition number	57	246	184	292	229
Intercept	6.195*** (0.493)	2.653* (1.548)	2.188* (1.127)	2.345* (1.256)	2.648** (1.032)
ln_palladium_price_in_2022_USD_per_oz_lag2	0.405*** (0.077)	-	-	0.334*** (0.072)	0.244*** (0.079)
ln_platinum_price_in_2022_USD_per_oz_lag2	-	-	-	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag2	-	0.617*** (0.156)	-	0.434*** (0.133)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag2	-	-	0.75*** (0.128)	-	0.521*** (0.138)
ln_total_supply_in_koz_lag1	-	-	-	-	-

Figure C.25: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 2 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6
Number of observations	40	40	40	40	40	40
R^2	0.434	0.3	0.466	0.581	0.581	0.602
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.001)	False (0.000)	False (0.010)	False (0.008)	False (0.004)
Breusch-Pagan passed? (p-value)	True (0.072)	True (0.142)	True (0.135)	True (0.056)	False (0.039)	True (0.542)
Shapiro-Wilk passed? (p-value)	True (0.100)	False (0.011)	True (0.186)	False (0.002)	False (0.020)	True (0.488)
Condition number	61	244	187	235	291	230
Intercept	6.03*** (0.514)	2.784* (1.488)	2.354** (1.119)	2.216* (1.152)	2.123* (1.175)	2.559** (0.980)
ln_palladium_price_in_2022_USD_per_oz_lag3	0.438*** (0.081)	-	-	0.265*** (0.086)	0.366*** (0.074)	0.283*** (0.079)
ln_platinum_price_in_2022_USD_per_oz_lag3	-	-	-	0.679*** (0.189)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag3	-	0.607*** (0.150)	-	-	0.441*** (0.122)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag3	-	-	0.735*** (0.128)	-	-	0.508*** (0.129)
ln_total_supply_in_koz_lag1	-	-	-	-	-	-

Figure C.26: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 3 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6
Number of observations	39	39	39	39	39	39
R^2	0.463	0.338	0.471	0.601	0.632	0.634
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.000)	False (0.000)	False (0.008)	False (0.008)	False (0.003)
Breusch-Pagan passed? (p-value)	False (0.010)	True (0.139)	True (0.084)	False (0.027)	False (0.020)	True (0.674)
Shapiro-Wilk passed? (p-value)	False (0.026)	False (0.019)	True (0.173)	False (0.006)	False (0.015)	True (0.959)
Condition number	64	241	186	233	288	229
Intercept	5.962*** (0.508)	2.813** (1.382)	2.647** (1.075)	2.506** (1.076)	2.036* (1.054)	2.675*** (0.907)
ln_palladium_price_in_2022_USD_per_oz_lag4	0.455*** (0.081)	-	-	0.27*** (0.088)	0.377*** (0.070)	0.307*** (0.077)
ln_platinum_price_in_2022_USD_per_oz_lag4	-	-	-	0.639*** (0.181)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag4	-	0.607*** (0.140)	-	-	0.446*** (0.110)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag4	-	-	0.705*** (0.123)	-	-	0.483*** (0.118)
ln_total_supply_in_koz_lag1	-	-	-	-	-	-

Figure C.27: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 4 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7
Number of observations	38	38	38	38	38	38	38
R^2	0.479	0.507	0.367	0.471	0.607	0.661	0.655
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.004)	False (0.001)	False (0.001)	False (0.012)	False (0.029)	False (0.012)
Breusch-Pagan passed? (p-value)	False (0.014)	True (0.784)	True (0.277)	False (0.031)	True (0.058)	False (0.048)	True (0.556)
Shapiro-Wilk passed? (p-value)	True (0.130)	False (0.000)	True (0.069)	True (0.719)	False (0.014)	True (0.050)	True (0.724)
Condition number	65	170	238	186	230	284	229
Intercept	5.983*** (0.499)	2.081* (1.110)	2.893** (1.303)	2.888*** (1.052)	2.812** (1.035)	2.136** (0.977)	2.779*** (0.861)
ln_palladium_price_in_2022_USD_per_oz_lag5	0.458*** (0.080)	-	-	-	0.268*** (0.090)	0.374*** (0.068)	0.318*** (0.073)
ln_platinum_price_in_2022_USD_per_oz_lag5	-	0.936*** (0.154)	-	-	0.603*** (0.178)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag5	-	-	0.601*** (0.132)	-	-	0.441*** (0.102)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag5	-	-	-	0.681*** (0.120)	-	-	0.467*** (0.110)
ln_total_supply_in_koz_lag1	-	-	-	-	-	-	-

Figure C.28: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 5 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2
Number of observations	42	37
R^2	0.954	0.709
Breusch-Godfrey passed? (p-value)	True (0.885)	True (0.083)
Breusch-Pagan passed? (p-value)	True (0.691)	True (0.084)
Shapiro-Wilk passed? (p-value)	True (0.564)	True (0.622)
Condition number	154	280
Intercept	0.556* (0.286)	2.268** (0.855)
ln_total_supply_in_koz_lag1	0.94*** (0.033)	-
ln_palladium_price_in_2022_USD_per_oz_lag6	-	0.362*** (0.062)
ln_platinum_price_in_2022_USD_per_oz_lag6	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag6	-	0.439*** (0.090)
ln_copper_price_in_2022_USD_per_metric_tonne_lag6	-	-

Figure C.29: Reliable and statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 6 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4
Number of observations	42	36	36	36
R^2	0.954	0.668	0.752	0.722
Breusch-Godfrey passed? (p-value)	True (0.885)	True (0.075)	True (0.231)	True (0.166)
Breusch-Pagan passed? (p-value)	True (0.691)	True (0.214)	True (0.099)	True (0.743)
Shapiro-Wilk passed? (p-value)	True (0.564)	False (0.021)	False (0.030)	True (0.365)
Condition number	154	225	276	230
Intercept	0.556* (0.286)	3.069*** (0.854)	2.335*** (0.744)	2.991*** (0.717)
ln_total_supply_in_koz_lag1	0.94*** (0.033)	-	-	-
ln_palladium_price_in_2022_USD_per_oz_lag7	-	0.236*** (0.078)	0.326*** (0.056)	0.308*** (0.061)
ln_platinum_price_in_2022_USD_per_oz_lag7	-	0.605*** (0.147)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag7	-	-	0.458*** (0.079)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag7	-	-	-	0.458*** (0.089)

Figure C.30: Reliable and statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 7 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5
Number of observations	42	35	35	35	35
R^2	0.954	0.686	0.751	0.73	0.916
Breusch-Godfrey passed? (p-value)	True (0.885)	True (0.067)	True (0.076)	True (0.105)	True (0.675)
Breusch-Pagan passed? (p-value)	True (0.691)	True (0.316)	True (0.399)	True (0.690)	True (0.963)
Shapiro-Wilk passed? (p-value)	True (0.564)	True (0.118)	False (0.015)	True (0.325)	True (0.174)
Condition number	154	223	272	232	289
Intercept	0.556* (0.286)	3.085*** (0.789)	2.631*** (0.703)	3.1*** (0.681)	0.766* (0.442)
ln_total_supply_in_koz_lag1	0.94*** (0.033)	-	-	-	0.778*** (0.073)
ln_palladium_price_in_2022_USD_per_oz_lag8	-	0.191** (0.073)	0.288*** (0.055)	0.281*** (0.058)	-
ln_platinum_price_in_2022_USD_per_oz_lag8	-	0.646*** (0.135)	-	-	0.172* (0.085)
ln_nickel_price_in_2022_USD_per_metric_tonne_lag8	-	-	0.455*** (0.075)	-	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag8	-	-	-	0.469*** (0.083)	-

Figure C.31: Reliable and statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 8 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6	7
Number of observations	34	42	34	34	34	34	34
R^2	0.607	0.954	0.669	0.717	0.726	0.655	0.645
Breusch-Godfrey passed? (p-value)	True (0.137)	True (0.885)	True (0.291)	True (0.354)	True (0.368)	True (0.228)	True (0.056)
Breusch-Pagan passed? (p-value)	True (0.150)	True (0.691)	True (0.325)	True (0.789)	True (0.307)	True (0.337)	True (0.102)
Shapiro-Wilk passed? (p-value)	False (0.015)	True (0.564)	False (0.015)	True (0.067)	True (0.258)	True (0.109)	True (0.077)
Condition number	166	154	221	268	231	299	266
Intercept	3.252*** (0.808)	0.556* (0.286)	3.518*** (0.761)	3.232*** (0.702)	3.438*** (0.651)	2.638*** (0.825)	2.906*** (0.803)
ln_platinum_price_in_2022_USD_per_oz_lag9	0.79*** (0.112)	-	0.607*** (0.129)	-	-	0.55*** (0.158)	0.542*** (0.174)
ln_palladium_price_in_2022_USD_per_oz_lag9	-	-	0.171** (0.071)	0.262*** (0.056)	0.258*** (0.056)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag9	-	-	-	0.414*** (0.074)	-	0.236** (0.114)	-
ln_copper_price_in_2022_USD_per_metric_tonne_lag9	-	-	-	-	0.45*** (0.078)	-	0.245* (0.135)
ln_total_supply_in_koz_lag1	-	0.94*** (0.033)	-	-	-	-	-

Figure C.32: Reliable and statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 9 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

	1	2	3	4	5	6
Number of observations	33	42	33	33	33	33
R^2	0.57	0.954	0.645	0.685	0.693	0.611
Breusch-Godfrey passed? (p-value)	True (0.089)	True (0.885)	True (0.163)	True (0.075)	True (0.272)	True (0.066)
Breusch-Pagan passed? (p-value)	True (0.066)	True (0.691)	True (0.249)	True (0.256)	True (0.165)	True (0.098)
Shapiro-Wilk passed? (p-value)	False (0.050)	True (0.564)	False (0.014)	True (0.352)	True (0.149)	True (0.210)
Condition number	165	154	218	264	231	295
Intercept	3.988*** (0.776)	0.556* (0.286)	4.219*** (0.723)	4.016*** (0.673)	4.136*** (0.636)	3.512*** (0.797)
ln_platinum_price_in_2022_USD_per_oz_lag10	0.692*** (0.108)	-	0.516*** (0.122)	-	-	0.481*** (0.158)
ln_palladium_price_in_2022_USD_per_oz_lag10	-	-	0.169** (0.067)	0.238*** (0.055)	0.246*** (0.054)	-
ln_nickel_price_in_2022_USD_per_metric_tonne_lag10	-	-	-	0.352*** (0.072)	-	0.201* (0.113)
ln_copper_price_in_2022_USD_per_metric_tonne_lag10	-	-	-	-	0.383*** (0.076)	-
ln_total_supply_in_koz_lag1	-	0.94*** (0.033)	-	-	-	-

Figure C.33: Reliable and statistically significant regression results for estimating the (cross) price elasticities of overall palladium supply using a time lag of 10 years for the prices. The coefficient estimates for the explanatory variables are displayed on the bottom 6 rows. The explanatory variable *ln_total_supply_in_koz_lag_1* refers to overall palladium supply in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

D

Appendix: The stockpiling mechanism

D.1. State stockpiling in the US

Year	Total size of palladium held by the NDS (in kg)	Data source
1995-1997	39300	(Hilliard, 1999b)
1998	38800	(Hilliard, 1999b)
1999	28200	(Hilliard, 1999b)
2000	19000	(George, 2004)
2001	16300	(George, 2004)
2002	5870	(George, 2004)
2003	1170	(George, 2004)
2004	568	(George, 2004)
2005-2013	0	Loferski, 2014b
2014-2018	less than 1 kg each of palladium and palladium-cobalt wire	(Loferski, 2015b; Loferski et al., 2016; Singerling, 2017; Singerling and Schulte, 2018)

Table D.1: Total size of palladium held by the US National Defense Stockpile at yearend during the period 1995-2018, as reported by the USGS.

E

Appendix: The substitution mechanism

E.1. Precious metals prices

Figure E.1 shows the annual real prices of three precious metals: palladium, platinum, and gold. Note that platinum and gold prices have typically been higher than the palladium price historically.

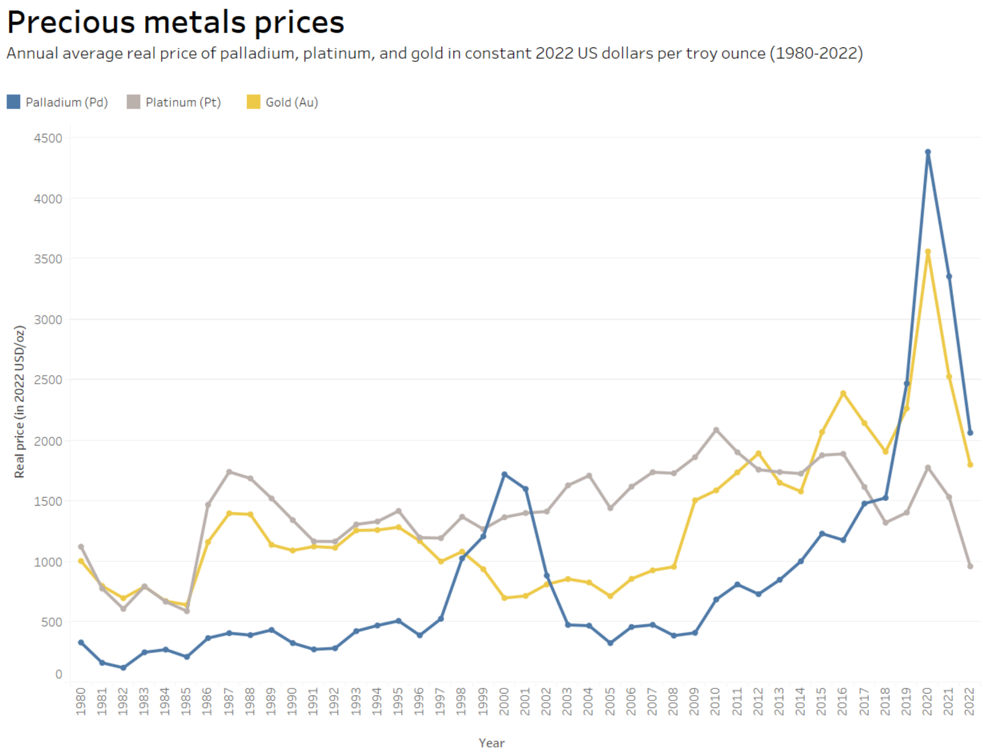

Figure E.1: Average annual real price of palladium, platinum, and gold in constant 2022 US dollars per troy ounce during the years 1980-2022. Figure based on own calculations using nominal prices from Macrotrends (2023) and the World Bank (2023b) and corrected for inflation using the Commodity Price Index (World Bank, 2023b).

E.2. Regression approach: (cross) price elasticities of demand

In mathematical terms, the regression models used to estimate the (cross) price elasticities of demand have the following generic equation (Nassar, 2015):

$$ln(D_{t,i}) = \alpha + \beta_{P,i}ln(P_t) + \sum_j \beta_{j,i}ln(X_{j,i}) + \epsilon_t$$

$D_{t,i}$ denotes the palladium demand in year t for application i. α is a constant term representing the palladium demand when all other parameters equal zero. $\beta_{P,i}$ is the price elasticity of demand for application i. P_t is the palladium price in year t, $\sum_{j,i} \beta_{j,i}ln(X_{j,i})$ is the sum of the contributions of all remaining explanatory variables. ϵ_t is the error term for year t.

For each palladium demand category (i.e. autocatalyst, chemical, dental and biomedical, electrical, jewellery, other, and overall), seven explanatory variables are considered:

- The logged real palladium price (in 2022 US dollars per troy ounce). In the regression results this variable is referred to as *ln_palladium_price_in_2022_USD_per_oz*.
- The logged real platinum price (in 2022 US dollars per troy ounce). In the regression results this variable is referred to as *ln_platinum_price_in_2022_USD_per_oz*.
- The logged real gold price (in 2022 US dollars per troy ounce). In the regression results this variable is referred to as *ln_gold_price_in_2022_USD_per_oz*.
- The logged real silver price (in 2022 US dollars per troy ounce). In the regression results this variable is referred to as *ln_silver_price_in_2022_USD_per_oz*.
- The logged real nickel price (in 2022 US dollars per metric tonne). In the regression results this variable is referred to as *ln_nickel_price_in_2022_USD_per_metric_tonne*.
- The logged real global GDP (in constant 2015 US dollars). In the regression results this variable is referred to as *ln_world_GDP_in_2015_USD*.
- The logged real gold price (in 2022 US dollars per troy ounce). In the regression results this variable is referred to as *ln_gold_price_in_2022_USD_per_oz*.
- The logged (application-specific) demand in the previous year (in koz). This explanatory variable is thus a lagged version of the dependent variable modelled.

E.3. Regression results: autocatalyst applications

All possible combinations of the eight explanatory variables were explored, resulting in 255[1] possible regression models. None of these regression models had significant coefficients for all explanatory variables at a 10% significance level and passed the Breusch-Godfrey and Breusch Pagan tests at a 5% significance level. Amongst the 255 regression models, 11 models do have significant coefficients for all explanatory variables. These statistically significant regression results are shown in Figure E.2. Note that these 11 models do not pass the Breusch-Godfrey and/or Breusch-Pagan tests. This implies that the residual errors of these models are auto-correlated and/or heteroscedastic, rendering these models unreliable.

[1]There are 256 (i.e. 2^8) possible combinations of eight explanatory variables. However, the combination of selecting no explanatory variables (i.e. intercept-only model) is not considered.

	1	2	3	4	5	6	7	8	9	10	11
Number of observations	43	43	43	43	43	43	43	43	43	43	43
R^2	0.315	0.142	0.856	0.417	0.661	0.661	0.661	0.894	0.916	0.908	0.917
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.000)	False (0.000)	False (0.000)	False (0.001)	False (0.001)	False (0.001)	False (0.000)	False (0.000)	False (0.000)	False (0.000)
Breusch-Pagan passed? (p-value)	True (0.683)	True (0.553)	True (0.211)	False (0.000)	False (0.011)	False (0.011)	False (0.011)	True (0.455)	True (0.419)	True (0.205)	True (0.426)
Shapiro-Wilk passed? (p-value)	False (0.017)	False (0.000)	False (0.035)	False (0.013)	False (0.007)	False (0.007)	False (0.007)	True (0.075)	True (0.399)	True (0.577)	True (0.488)
Condition number	176	27	2658	3	237	162	179	3234	4311	3797	4478
Intercept	-10.517** (4.186)	3.436** (1.619)	-98.28*** (6.778)	8.624*** (0.245)	-7.535** (3.016)	-7.535** (3.016)	-7.535** (3.016)	-112.535*** (6.984)	-95.66*** (8.241)	-102.781*** (7.748)	-93.9*** (8.550)
ln_platinum_price_in_2022_USD_per_oz	2.512*** (0.579)	-	-	-	1.078** (0.469)	-	2.226*** (0.415)	-	-	-	0.667** (0.318)
ln_palladium_price_in_2022_USD_per_oz	-	-	-	-	1.148*** (0.179)	2.226*** (0.415)	-	-	0.432*** (0.136)	-	-
ln_gold_price_in_2022_USD_per_oz	-	-	-	-	-	-	-	-0.872*** (0.230)	-1.07*** (0.217)	-0.958*** (0.220)	-1.112*** (0.224)
ln_silver_price_in_2022_USD_per_oz	-	1.416** (0.543)	-	-	-	-	-	-	-	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne	-	-	-	-	-	-	-	-	-	-	-
ln_world_GDP_in_2015_USD	-	-	3.359*** (0.215)	-	-	-	-	4.008*** (0.253)	3.429*** (0.292)	3.725*** (0.267)	3.329*** (0.318)
ln_demand_auto_in_koz_lag1	-	-	-	-	-	-	-	-	-	-	-
ln_palladium_to_platinum_price_ratio	-	-	-	1.252*** (0.231)	-	-1.078** (0.469)	1.148*** (0.179)	-	-	0.295** (0.123)	0.443*** (0.137)

Figure E.2: Statistically significant regression results for estimating the (cross) price elasticities of palladium autocatalyst demand. The coefficient estimates for the explanatory variables are displayed on the bottom 8 rows. The explanatory variable *ln_palladium_to_platinum_price_ratio* refers to the logged palladium-platinum price ratio.The explanatory variable *ln_demand_auto_in_koz_lag_1* refers to the logged palladium autocatalyst demand in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

E.4. Regression results: chemical applications

All possible combinations of the seven explanatory variables were explored, resulting in 127[2] possiblr regression models. None of these regression models had significant coefficients for all explanatory variables at a 10% significance level and passed the Breusch-Godfrey and Breusch Pagan tests at a 5% significance level. Amongst the 127 regression models, four models do have significant coefficients for all explanatory variables. These statistically significant regression results are shown in Figure E.3. Note that these four models do not pass the Breusch-Godfrey test. This implies that the residual errors of these models are auto-correlated, rendering these models unreliable.

	1	2	3	4
Number of observations	37	37	37	37
R^2	0.388	0.362	0.911	0.481
Breusch-Godfrey passed? (p-value)	False (0.000)	False (0.002)	False (0.011)	False (0.002)
Breusch-Pagan passed? (p-value)	True (0.635)	True (0.562)	True (0.140)	True (0.262)
Shapiro-Wilk passed? (p-value)	True (0.127)	True (0.658)	True (0.055)	True (0.766)
Condition number	63	27	3142	74
Intercept	3.438*** (0.489)	3.793*** (0.436)	-31.747*** (1.985)	3.015*** (0.487)
ln_palladium_price_in_2022_USD_per_oz	0.347*** (0.074)	-	-	0.231*** (0.083)
ln_platinum_price_in_2022_USD_per_oz	-	-	-	-
ln_gold_price_in_2022_USD_per_oz	-	-	-	-
ln_silver_price_in_2022_USD_per_oz	-	0.651*** (0.146)	-	0.399** (0.161)
ln_nickel_price_in_2022_USD_per_metric_tonne	-	-	-	-
ln_world_GDP_in_2015_USD	-	-	1.185*** (0.063)	-
ln_demand_chemical_in_koz_lag1	-	-	-	-

Figure E.3: Statistically significant regression results for estimating the (cross) price elasticities of palladium autocatalyst demand. The coefficient estimates for the explanatory variables are displayed on the bottom 7 rows. The explanatory variable *ln_demand_chemical_in_koz_lag_1* refers to the logged palladium chemical demand in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

[2]There are 128 (i.e. 2^7) possible combinations of seven explanatory variables. However, the combination of selecting no explanatory variables (i.e. intercept-only model) is not considered.

E.5. Regression results: overall palladium demand

All possible combinations of the seven explanatory variables were explored, resulting in 127 possible regression models. None of these regression models had significant coefficients for all explanatory variables at a 10% significance level, included at least one price-related explanatory variable, and passed the Breusch-Godfrey and Breusch Pagan tests at a 5% significance level. Amongst the 127 regression models, nine models do have significant coefficients for all explanatory variables. These statistically significant regression results are shown in Figure E.4. Note that model 5 does have statistically significant coefficients for all explanatory variables and passes the Breusch-Godfrey and Breusch-Pagan tests at a 5% significance level. This model has only one explanatory variable: logged overall palladium demand in the previous year. Since this model does not contain any price-related variables, this model does not provide insight into price elasticity and substitution. Accordingly, this model is not discussed in Chapter 8. Moreover, note that the remaining eight statistically significant models do not pass the Breusch-Godfrey and/or Breusch-Pagan tests. This implies that the residual errors of these models are auto-correlated and/or heteroscedastic, rendering these models unreliable.

	1	2	3	4	5	6	7	8	9
Number of observations	43	43	43	43	42	43	43	43	43
R^2	0.607	0.282	0.127	0.856	0.95	0.872	0.87	0.886	0.898
Breusch-Godfrey passed? (p-value)	False (0.001)	False (0.000)	False (0.000)	False (0.000)	True (0.237)	False (0.000)	False (0.000)	False (0.000)	False (0.000)
Breusch-Pagan passed? (p-value)	True (0.203)	False (0.002)	True (0.626)	True (0.435)	True (0.215)	True (0.284)	True (0.538)	True (0.060)	True (0.068)
Shapiro-Wilk passed? (p-value)	True (0.578)	True (0.152)	False (0.001)	False (0.001)	True (0.176)	False (0.001)	False (0.002)	True (0.105)	False (0.028)
Condition number	54	125	27	2658	147	3234	2936	4311	4560
Intercept	5.404*** (0.417)	3.921*** (1.193)	7.183*** (0.628)	-31.996*** (2.605)	0.615** (0.295)	-35.58*** (2.947)	-34.337*** (2.759)	-30.417*** (3.685)	-28.471*** (3.646)
ln_palladium_price_in_2022_USD_per_oz	0.513*** (0.064)	-	-	-	-	-	-	0.132** (0.061)	0.144** (0.059)
ln_platinum_price_in_2022_USD_per_oz	-	-	-	-	-	-	-	-	0.248** (0.117)
ln_gold_price_in_2022_USD_per_oz	-	0.673*** (0.168)	-	-	-	-0.219** (0.097)	-	-0.28*** (0.097)	-0.326*** (0.095)
ln_silver_price_in_2022_USD_per_oz	-	-	0.513** (0.211)	-	-	-	-0.193** (0.095)	-	-
ln_nickel_price_in_2022_USD_per_metric_tonne	-	-	-	-	-	-	-	-	-
ln_world_GDP_in_2015_USD	-	-	-	1.291*** (0.083)	-	1.454*** (0.107)	1.383*** (0.092)	1.277*** (0.131)	1.166*** (0.136)
ln_total_demand_in_koz_lag1	-	-	-	-	0.934*** (0.034)	-	-	-	-

Figure E.4: Statistically significant regression results for estimating the (cross) price elasticities of overall palladium demand. The coefficient estimates for the explanatory variables are displayed on the bottom 7 rows. The explanatory variable *ln_total_demand_in_koz_lag_1* refers to the logged overall palladium demand in the previous year (in koz). For the coefficient estimates, the number in parentheses indicates the standard error and *,**, and *** indicate 10%, 5%, and 1% significance, respectively.

F

Appendix: Policy implications

F.1. Correlation matrix of indicators

In Chapter 9, eight indicators were identified that were deemed suitable for inclusion in the compound resilience index:

1. **Country-level diversity of reserves** = 10,000 – country-level HHI of PGM reserves.
2. **Country-level diversity of mining** = 10,000 – country-level HHI of primary palladium production.
3. **Facility-level diversity of mining** = 10,000 – facility-level HHI of primary palladium production.
4. **Company-level diversity of mining** = 10,000 – company-level HHI of primary palladium production.
5. **EOL-RIR**.
6. **Country-level diversity of exports** = 10,000 – country-level HHI of net exports of refined palladium.
7. **Percentage of palladium mined as host metal** = 1 – companionality.
8. **Size of total stockpiles in months of demand**.

Recall from Chapter 5 that both the lower and upper bounds were computed for the facility-level and company-level concentrations of primary palladium production. These lower and upper bounds for the production concentrations correspond to upper and lower bounds for the diversity of mining indicators, respectively. Hence two different values are considered for both the facility-level diversity of mining and the company-level diversity of mining indicators: a lower bound and an upper bound. The lower and upper bound of the same indicator are obviously not included in the same index.

Inclusion of all indicators in the compound index would lead to double counting and overrepresentation of of some resilience mechanisms in the compound resilience index. Therefore, following Savelberg (2022), indicators with a Pearson correlation coefficient larger than 0.7 are removed. Based on the correlation matrix (see Figure F.1) of the indicators, five pairs of indicators are identified that have a correlation exceeding 0.7: the company-level diversity of mining lower and upper bounds, the EOL-RIR and the country-level diversity of reserves, the EOL-RIR and the facility-level diversity of mining (upper bound), the EOL-RIR and the percentage of palladium mined as host metal, and the country-level diversity of reserves and the percentage of palladium mined as host. Accordingly, these highly correlated indicators are not considered for inclusion in the same index composition. The section below explores the implications of using different index compositions.

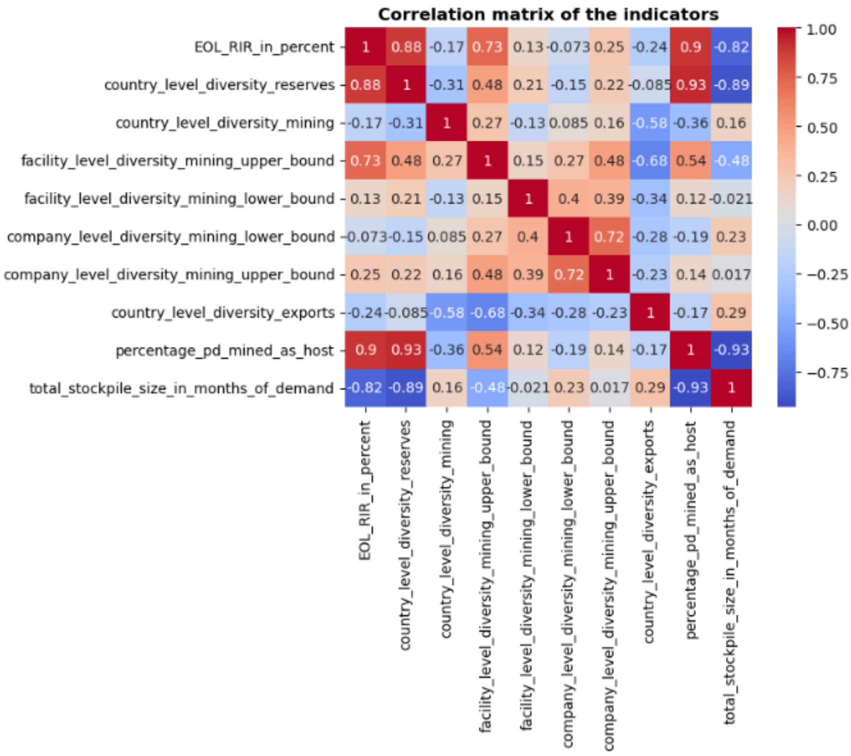

Figure F.1: Correlation matrix of the indicators considered for index inclusion. Note that a distinction is made between the upper and lower bound values for the facility-level and company-level diversity of mining indicators. For example, *facility_level_diversity_mining_lower_bound* refers to the facility-level diversity of mining computed based on the lower bound value of the facility-level HHI of primary palladium production.

F.2. Sensitivity analysis: resilience index

Several different index compositions are possible that exclude the highly-correlated indicators identified in the section above. For the index discussed in the main text, it is decided to remove the EOL-RIR and the country-level diversity of reserves as indicators and compute the index based on the six remaining indicators. The rationale behind selecting this index composition of indicators is that it minimises the number of removed indicators, while keeping the only indicator associated with the price mechanism (i.e. the percentage of palladium mined as host metal). However, alternative index compositions that also exclude highly-correlated indicators are also possible. six different index compositions are explored:

- Index composition 1 (index used in the main text). This index consists of six indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, facility-level diversity of mining (upper bound), company-level diversity of mining (upper bound), percentage palladium mined as host.
- Index composition 2. This index consists of six indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, facility-level diversity of mining (lower bound), company-level diversity of mining (lower bound), percentage palladium mined as host.
- Index composition 3. This index consists of six indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, facility-level diversity of mining (upper bound), company-level diversity of mining (upper bound), country-level diversity of reserves.
- Index composition 4. This index consists of six indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, facility-level diversity of mining (lower bound), company-level diversity of mining (lower bound), country-level diversity of reserves.

- Index composition 5. This index consists of six indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, facility-level diversity of mining (lower bound), company-level diversity of mining (lower bound), EOL-RIR.
- Index composition 6. This index consists of five indicators: country-level diversity of mining, country-level diversity of exports, size of total stockpiles in months of demand, company-level diversity of mining (upper bound), EOL-RIR.

This exploration of the six different index compositions can be considered as a simple sensitivity and uncertainty analysis. Sensitivity analysis, because the impact on the resilience index is explored for two different values (a lower and upper bound) of the facility-level and company-level diversity of mining indicators. Uncertainty analysis, because the impact on the resilience index score is explored for different assumptions about the structural composition of the index. Note that for each index composition, different PCA-based weights for the indicators are obtained. The resulting resilience index scores for the six different index compositions are shown in Figure F.2. Note that for all six different index compositions the resilience score was higher in 2021 than it was in 2012. This indicates that for the period 2012-2021 overall, resilience improved.

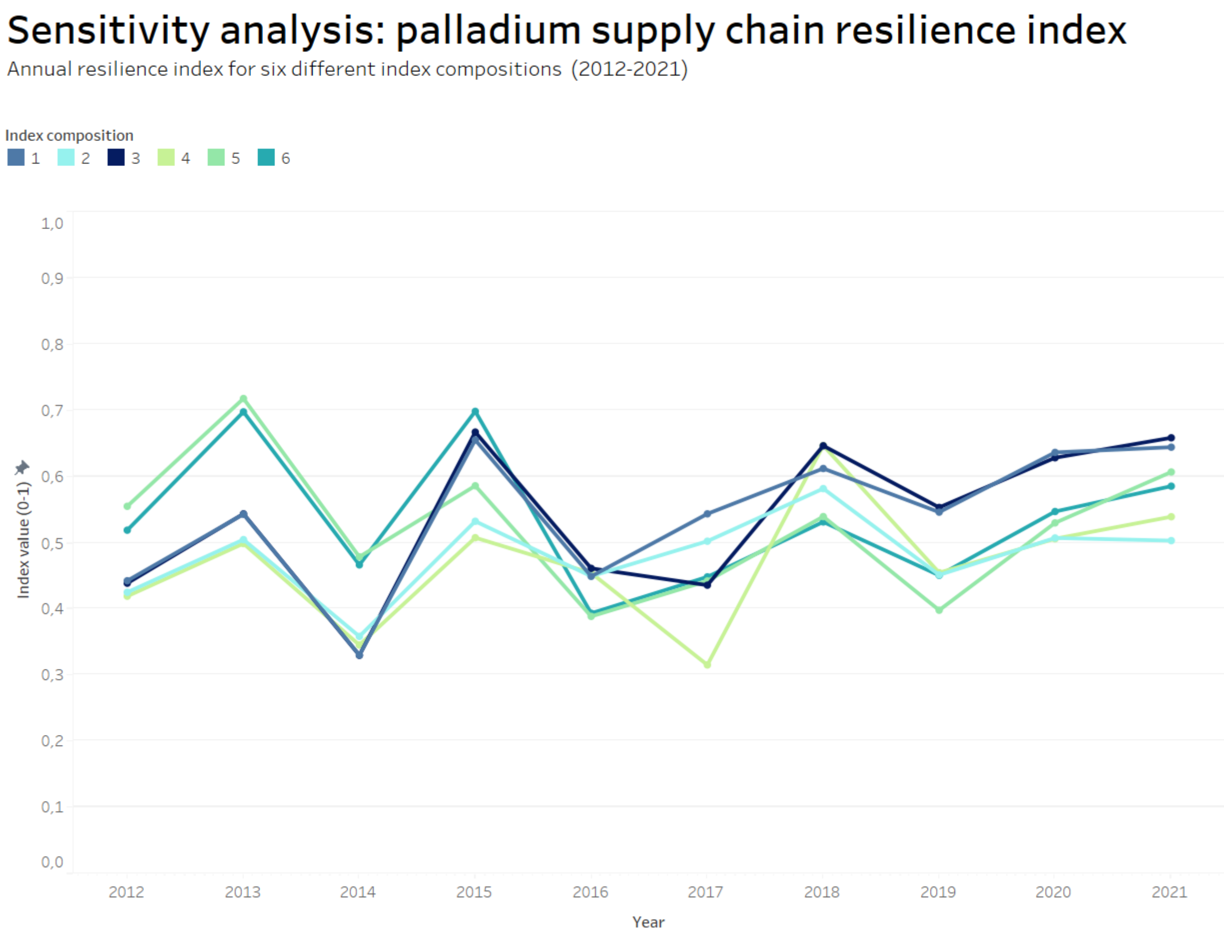

Figure F.2: Annual resilience index score for six different index compositions during the years 2012-2021. The index score is computed based on PCA-weighting. Note that index composition 1 corresponds to the resilience index presented in the main text.