Impact of roadworks severity on commuters' mode choice and working from home

Evidence from Stated and Revealed Behaviour in the Netherlands

Splinter Groenink

Delft University of Technology

Impact of roadworks severity on commuters' mode choice and working from home

Evidence from Stated and Revealed Behaviour in the Netherlands

by

Splinter Groenink

Supervision:	Dr.ir. A.J. (Adam) Pel
Supervision:	Dr.ir. M. (Maarten) Kroesen
Supervision (Sweco):	Dr.ir. K. (Koen) de Clercq
Project Duration:	September 2025 – March 2026
Faculty:	Civil Engineering & Geosciences, Delft

Preface

This thesis is submitted in partial fulfilment of the requirements for the Master of Science programme in Transport Infrastructure and Logistics at TU Delft. The research was conducted in collaboration with Sweco and focuses on how working commuters in the Netherlands adapt to planned temporary roadworks, with specific attention to disruption severity, mode choice, and working from home.

I would like to express my sincere gratitude to my academic supervisors at TU Delft, Maarten Kroesen and Adam Pel, for their guidance throughout the research process. Their critical feedback and support helped me sharpen the research design, strengthen the analysis, and improve the clarity of the thesis. I also thank Koen de Clercq and my colleagues at Sweco for their practical insights and discussions, which helped bridge the gap between academic work and professional practice.

I am grateful to all survey respondents who took the time to participate and share information about their commuting and work situations. Without their input, this study would not have been possible. In addition, I thank my friends and family, who supported me during the thesis period, for their encouragement and patience.

Splinter Groenink
Delft, March 2026

Summary

The Netherlands faces a dual mobility challenge. Road traffic and congestion have largely recovered after the pandemic, while a wave of life-extension and renewal works on ageing bridges, tunnels, and motorway sections is planned for the coming years. This combination increases the likelihood of repeated, severe, but temporary disruption episodes. At the same time, working patterns have changed structurally. A substantial share of Dutch workers work from home at least occasionally, making working from home (WFH) a plausible non-travel adaptation strategy when commuters face major but time-limited roadwork disruptions.

Understanding when commuters continue to drive, switch to public transport, or work from home instead of travelling is relevant to traffic management and demand forecasting. If non-travel responses are not explicitly represented, traffic models may overestimate detour-route congestion and mischaracterise the impacts of roadworks and associated closures. A related aggregate phenomenon is "disappearing traffic", referring to reductions in motor-vehicle volumes after capacity constraints that are not fully displaced elsewhere. This is not a mechanism in itself, but the outcome of behavioural adjustments such as WFH and mode switching. The empirical focus of this thesis is therefore on two adaptation channels that may partly explain this reduction during planned roadworks: working from home and switching from car to public transport.

This study investigates how disruption severity shapes these responses among working commuters in the Netherlands. The main research question is:

How does the severity of temporary roadworks disruptions shape working commuters' mode choice and working from home responses in the Netherlands?

To address this question, the thesis combines a focused literature synthesis with an online survey that captures both stated intentions in controlled scenarios and self-reported realised behaviour during experienced disruptions. The literature suggests that disruption responses are often hierarchical rather than singular: commuters may first try to preserve car use through intramodal adaptations such as rerouting and retiming, while intermodal switching and non-travel responses become more likely when disruption costs become sufficiently salient. This framing motivates the empirical focus on mode shift to public transport and WFH as the two adaptation channels examined in detail.

The empirical core consists of an online questionnaire administered to employed commuters who travel to a workplace at least once per week. The survey integrates three complementary modules. First, an attribute-based stated-choice experiment asks respondents to choose, for a stylised "next working day" roadworks scenario, between continuing by car, switching to public transport, or working from home. Second, a pivot experiment is administered to respondents who typically commute by car and have a car available; in this module, disruption severity is anchored to each respondent's reported commute time via percentage increases, after which respondents again choose between car, PT, and WFH. Third, a revealed-preference module asks the same car-commuter group whether they experienced substantial hindrance from major roadworks or closures in recent years and, if so, which of these three broad responses they actually used. Across the survey, disruption severity is operationalised primarily as increased car travel time, motivated and benchmarked using Dutch roadworks information and a network-impact case study. Together, the modules are designed to identify the direction and relative severity of effects, possible threshold-like nonlinearity, and the role of constraints and heterogeneity in shaping substitution away from the car.

The final analytical sample consists of 180 respondents after a sequence of quality and plausibility filters. Benchmarking indicates that the sample is not population-representative and is skewed toward younger and more highly educated respondents. This matters substantively because flexibility and WFH feasibility are unevenly distributed in the wider population. Within the sample, WFH feasibility is relatively high, and many respondents report at least some flexibility in working arrangements, while

fixed on-site obligations remain present for part of the sample. This makes the sample particularly informative for studying constraint-gated WFH responses: WFH may be technically feasible but remains limited by workplace expectations and on-site requirements.

The results indicate that higher disruption severity is associated with lower persistence in car commuting and a shift toward two substitutes: WFH and, to a lesser extent, public transport. Importantly, the descriptive pivot shares suggest that adaptation does not increase proportionally with disruption severity, with the clearest shift occurring between low and medium severity. In the pivot experiment, small disruptions often fall within a tolerance range in which most commuters continue driving, whereas stronger disruptions are associated with a clearer shift toward adaptation. In the observed pivot choice shares shown in Figure 1, the clearest transition occurs between low and medium severity: car choice declines noticeably, while both WFH and PT increase. At high severity, WFH appears to become the dominant substitute when feasible, while PT becomes more relevant once disruption costs are sufficiently large to overcome part of the baseline resistance to switching.

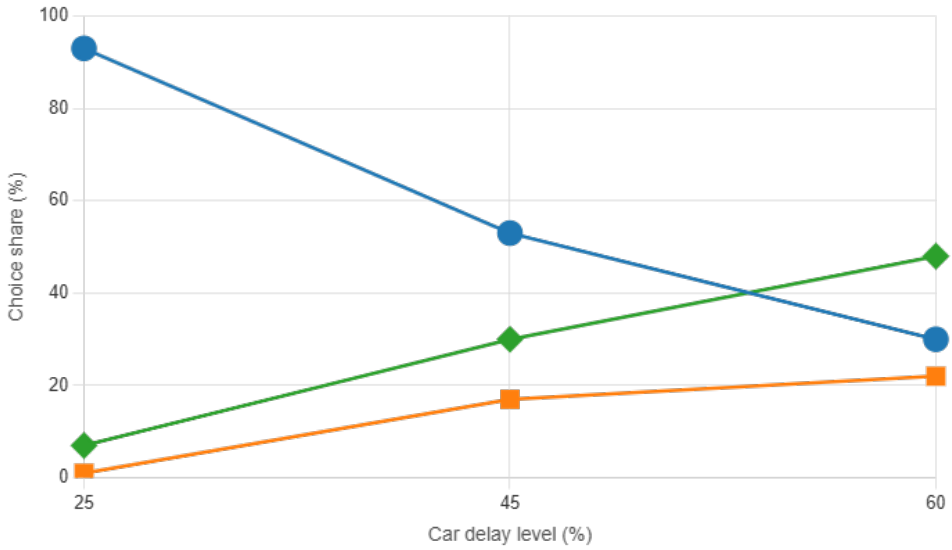


Figure 1: Pivot choice shares per severity level

A second central finding is that WFH functions as a constraint-gated channel rather than a universally available substitute. Across model estimates and scenario patterns, WFH uptake is shaped strongly by whether work can realistically be performed from home and whether on-site presence is required. Where on-site obligations are binding, increased disruption translates into less WFH; instead, substitution away from the car is more likely through PT, provided PT is a realistic option. Conversely, among commuters with greater work flexibility, severity-induced adaptation is channelled more strongly into WFH. In this sense, severity appears to determine the pressure to adapt, while constraints largely determine which alternative absorbs that response. These predicted probabilities should be interpreted as scenario-conditional stated responses under controlled assumptions about disruption severity, rather than as direct forecasts of realised behaviour during actual roadworks. The relatively high adaptation probabilities among more flexible workers, therefore, reflect a greater stated capacity to substitute out of commuting when disruption costs rise, while location-bound workers remain more car-persistent because on-site obligations limit WFH. This interpretation is consistent with the revealed-preference evidence, which shows higher real-world car persistence overall and suggests that the magnitudes in Figure 2 should be read as indicative of behavioural structure rather than exact realised switching rates.

Beyond these constraints, the analysis suggests meaningful heterogeneity in both sensitivities and baseline propensities. Discrete choice models estimated on the stated-choice data indicate that the car option becomes less attractive as travel time and costs increase, while PT uptake remains limited by strong baseline barriers in the sample. Heterogeneity analyses further suggest that a single population-average response function masks substantial variation among commuters: some are highly delay-sensitive and switch earlier, whereas others exhibit greater inertia unless the disruption becomes

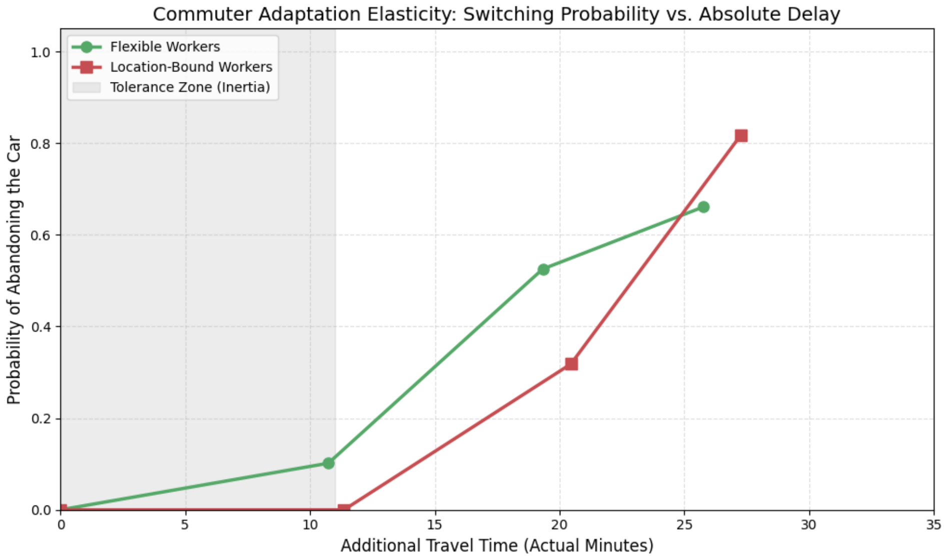


Figure 2: Commuter adaptation elasticity: probability of switching to an alternative (PT or WFH) as a function of absolute delay

more extreme. Even among commuters for whom WFH is feasible, baseline WFH propensity varies, indicating that disruption activates WFH for some but not all feasible individuals. This variation helps explain why similar increases in travel-time burden can elicit different responses among commuters.

The revealed-preference module provides an empirical check on realised behaviour during experienced disruptions and points to an important intention–behaviour gap. While the stated-choice scenarios indicate substantial willingness to switch away from the car under higher severity, self-reported realised behaviour during experienced disruptions shows considerably higher car persistence. Among those who reported changing behaviour in real-world experiences, WFH was reported more frequently than switching to PT. Because the revealed-preference module does not measure disruption magnitude and duration in comparable units, this evidence is best interpreted as indicating stronger real-world inertia and transaction costs rather than enabling one-to-one calibration of severity-specific elasticities. It nevertheless supports a cautious interpretation of predicted switching magnitudes and reinforces the emphasis on qualitative behavioural mechanisms over point estimates.

Overall, the findings suggest that the main contribution of this thesis lies less in predicting exact switching magnitudes and more in identifying the behavioural structure through which commuters respond to planned roadworks. Disruption severity appears to create the pressure to adapt, but the realised response is strongly shaped by constraints and heterogeneity: when WFH is feasible and on-site requirements are limited, adaptation is channelled primarily into WFH, whereas under stronger location-bound constraints, substitution is more likely to occur through public transport, if feasible at all. In this sense, the thesis shows that "disappearing traffic" during roadworks should not be interpreted as a uniform reduction in demand, but as the outcome of differentiated behavioural mechanisms.

From a practical perspective, these findings imply that roadworks impact assessments and mitigation strategies should not treat commuter adaptation as a uniform response. Instead, planners and modellers should account for the fact that stronger disruption severity can trigger substitution away from car travel, but that the dominant response depends heavily on contextual constraints, particularly WFH feasibility and on-site work requirements. This means that forecasts based solely on rerouting or static mode-shift assumptions may misrepresent actual behavioural adaptation, while effective mitigation may require severity-specific and group-specific measures, such as combining traffic management with employer-oriented WFH facilitation and targeted public transport support where switching is realistically feasible.

At the same time, these conclusions should be interpreted with appropriate caution. The strongest evidence concerns the direction and structure of behavioural responses rather than their exact real-world magnitude, because the core severity evidence is derived from stated-choice scenarios and the revealed-preference module is not conditioned on comparable disruption magnitudes. In addition, the analytical sample is not population-representative, and the empirical choice set does not explicitly include intramodal adaptations such as rerouting and retiming. The thesis therefore provides the greatest confidence in the conclusion that planned roadworks can trigger threshold-like substitution away from routine car use, while the precise scale and distribution of that response should be further validated using more representative and severity-linked revealed data. Future research should therefore validate these behavioural patterns using more representative and severity-linked revealed data, while also examining how intramodal responses such as rerouting and retiming interact with WFH and mode switching.

Contents

1 Introduction

The Netherlands faces a dual mobility challenge. Road traffic volumes and congestion have rebounded after the pandemic. At the same time, a wave of life-extension and renewal works on ageing bridges, tunnels and motorway sections is scheduled for the coming years. The motoring organisation ANWB reports that congestion severity on Dutch roads increased by approximately 8% in 2024 compared to 2023, with delays increasingly occurring outside the traditional peak periods (ANWB, 2024). In September 2025, ANWB further reported a 19% year-on-year increase in ”filezwaarte” (length × duration), including a 34% rise in the morning peak (ANWB-verkeersinformatie, 2025). In parallel, Rijkswaterstaat anticipates substantial, recurring impacts on the network due to the national ”Vervanging en Renovatie” programme. This programme involves more than a hundred civil assets built in the 1950s–1970s that require replacement or refurbishment, with works already planned and communicated (Ministerie van Infrastructuur en Waterstaat, 2025a). Together, rising demand and intensive work make the management of traveller responses to temporary roadworks and associated road closures a policy and modelling problem. These network pressures coincide with evolving work patterns, which reshape how people respond to disruptions.

At the same time, the organisation of work has undergone a structural shift. In 2023, more than half of Dutch workers (52%) reported working from home at least sometimes. This was the highest share in the EU at that time. However, the share of people who usually work from home declined from its pandemic peak (CBS, 2024). For a substantial fraction of working commuters who typically drive, non-travel options such as working from home (WFH) have become a realistic adaptation strategy when faced with severe, time-limited network disruptions.

Understanding when commuters decide to continue commuting by car, switch to public transport, or work from home instead of travelling is fundamental to traffic management during the workday, accurate demand forecasting, and the evaluation of mitigation packages. Without quantifying these ”non-travel” responses, traffic models may overestimate congestion on detour routes, leading to inaccurate impact assessments.

A related concept is disappearing traffic, also referred to as traffic evaporation, an empirically observed reduction in motor-vehicle volumes following capacity constraints or road-space reallocation that is not entirely displaced elsewhere in the network. Importantly, disappearance is not a direct measure but rather an aggregated outcome of mechanisms such as working from home, rescheduling activities, and destination substitution (Cairns et al., 2001; Calvert & Melia, 2023). In this thesis, the empirical focus is on two key mechanisms behind such disappearance, working from home and mode shift from car to public transport, rather than broader adaptations such as destination substitution or activity rescheduling.

In the post-COVID context of widespread hybrid work, non-travel responses may be more dominant and more manageable to leverage in policy during temporary closures. The pandemic rapidly normalised working from home, establishing the necessary technical infrastructure and cultural acceptance for it to become a persistent part of commuting patterns (Ashour & Shen, 2025). Consequently, WFH is now a highly viable, flexible adaptation strategy.

Recent Dutch research linking increased travel time to fewer car trips provides a valuable starting point. Using a stated-preference survey among urban car users, the study found that a realistic increase of 5 to 10 minutes in travel time could lead to approximately 10% of car traffic ”disappearing”. Crucially, for work-related trips, respondents were significantly more likely to cancel the trip entirely than to switch to another mode of transport. However, it was not designed with closure duration in mind and did not distinguish WFH from other work arrangements (van Dijk, 2022). This leaves several unaddressed gaps in understanding how the severity of temporary closures influences the likelihood of WFH or other behavioural adaptations in the Dutch context.

1.1. Problem statement

Despite the growing practical importance of temporary roadworks, existing planning and modelling practice in the Netherlands still relies on simplified assumptions. In many project appraisals and traffic studies, the impact of major works is represented by generic demand-reduction factors or ad hoc adjustments to route choice in traffic models, with limited empirical justification. These approaches typically focus on traffic that continues to travel and treat any “disappearing” demand as a residual. WFH and other non-travel responses are rarely modelled explicitly, and the role of disruption duration is often ignored (de Clercq, 2025). The literature review in this thesis identifies several substantive gaps. First, disruption severity is seldom treated as a multidimensional construct. In specific case settings, additional travel time may interact with the disruption’s temporal context (time of day and commute direction), making it relevant to examine whether this context adds explanatory value once the disruption’s core travel burden is taken into account. Second, non-travel responses such as WFH, trip cancellation and substantial schedule changes are structurally under-represented in behavioural models, because standard data sources primarily observe realised trips rather than decisions to stay at home. Third, the empirical base is heavily skewed towards pre-COVID case studies in North American and UK contexts, with relatively little quantitative evidence for dense, multimodal urban regions with widespread hybrid working, such as the Dutch setting.

As a result, planners and consultants lack robust evidence on how different groups of commuters respond to temporary road closures of varying severity and on the extent to which WFH can mitigate peak-period congestion during the workday. In the Dutch post-COVID context, where hybrid work arrangements are common and dense multimodal networks offer several alternatives, this thesis aims to provide quantitative insight into how disruption severity in temporary roadworks reshapes mode choice and WFH responses among working commuters, how these responses differ across individuals and constraints, and whether temporal context adds explanatory power beyond the increase in car travel time itself. Disruption severity is operationalised primarily as increased car travel time, while temporal context is incorporated through scenario timing (time of day and commute direction) and empirically grounded using Dutch roadworks data and a network case study. Closure duration is used for descriptive grounding rather than as an explicitly modelled choice attribute.

1.2. Research question

This thesis investigates how temporary roadworks and associated road closures affect working commuters’ mode choice, with particular attention to working from home as a non-travel response. In this thesis, working from home (WFH) is used as the operational term for the non-travel work response in the survey. In the literature, comparable behaviour is often referred to as telework or telecommuting. For clarity and consistency, this thesis uses WFH throughout the empirical chapters, except for references to the literature in the academic context.

How does the severity of temporary roadworks disruptions shape working commuters’ mode choice and WFH responses in the Netherlands?

This research question is addressed through a set of sub-questions that together structure the analysis of commuter adaptation to planned temporary roadworks. The sub-questions first establish the relevant behavioural effects of roadworks on commuting and the role of working from home as an adaptation option. They then examine how increasing disruption severity shifts car commuters' choices towards public transport or working from home, and finally explain why these responses differ across commuters by considering constraints and behavioural heterogeneity.

Sub-questions

1. What are the relevant effects of planned temporary roadworks on commuting behaviour?
2. Which factors are associated with working from home during planned roadworks disruptions?
3. How does disruption severity affect the likelihood that car commuters switch to public transport or choose working from home?
4. Which factors explain differences in responses to planned roadworks disruptions?

Together, these questions translate the conceptual gap identified in the introduction into an empirical framework that guides survey design and the modelling approach presented in the following chapters.

1.3. Overview of methods

This thesis combines three complementary methodological components. A systematic literature review synthesises existing empirical evidence on travel behaviour under temporary roadworks. Empirical roadworks data from the Dutch National Traffic Data Portal (NDW), complemented by a network case study, characterise disruption severity in the Dutch context. Finally, a combined stated- and revealed-preference survey among working commuters, analysed using discrete-choice models, quantifies how disruption severity and individual context shape mode choice and WFH responses. Survey responses are analysed using discrete choice models, including Multinomial Logit (MNL), Mixed Logit (MXL), and Latent Class specifications, to quantify average effects and heterogeneity.

Table 1.1: Methodology for Research Sub-Questions

Sub-Question	Proposed Methods
1. What are the relevant effects of planned temporary roadworks on commuting behaviour?	Systematic literature review
2. Which factors are associated with working from home during planned roadworks disruptions?	Survey data, descriptive analysis
3. How does disruption severity affect the likelihood that car commuters switch to public transport or choose working from home?	Survey data, MNL
4. Which factors explain differences in responses to planned roadworks disruptions?	Survey data, MXL and Latent Class

1.3.1. Literature review

The literature review identifies how temporary roadworks and related capacity reductions affect commuting behaviour, and which factors drive mode shifts and non-travel responses. It follows a structured search and screening procedure and draws on guidance for narrative and systematic reviews in transport and social sciences (Snyder, 2019). The review provides the theoretical foundation for the conceptual framework, informs the formulation of the stated-preference attributes, and highlights empirical gaps that motivate the research questions.

1.3.2. NDW roadworks data analysis & network case study

To ensure that the stated-choice experiment is anchored in a realistic Dutch context, national roadworks registrations from the National Data Warehouse for Traffic Information (NDW) are used as an external reference for how planned works are typically characterised in practice. This serves two purposes. First, it provides a consistent definition of severity that aligns with how disruptions are communicated and managed in the Netherlands, rather than relying on arbitrary or purely theoretical labels. Second, it supports the study's internal validity by ensuring that the experimental scenarios reflect the range and combinations of disruption characteristics that commuters are likely to recognise as credible.

In addition, a network-based case study is used to estimate the likely impact of roadworks in a Dutch context and to translate this into realistic attribute levels for the experiment. NDW registrations describe planned works in operational terms, whereas respondents must evaluate scenarios in traveller-relevant quantities, most importantly, in terms of additional travel time. The case study, therefore, provides an empirical basis for selecting plausible level ranges, ensuring that the stated-choice tasks reflect impacts that commuters could realistically experience during planned roadworks in the Netherlands.

1.3.3. Survey design

The empirical core of the thesis is an online survey among working commuters in the Netherlands. The roadworks data and case study described in Chapter 3 provide realistic ranges for disruption severity, which are used to define attribute levels in the stated-preference experiments. The survey combines stated-preference (SP) and revealed-preference (RP) components. Two SP choice experiments expose respondents to hypothetical roadwork scenarios in which they choose between continuing by car, switching to public transport (PT), or working from home. An attribute-based experiment varies travel time and travel cost across alternatives, while a pivoted experiment varies travel time relative to each respondent's usual commute. SP methods are widely used in transport research because they allow controlled variation in disruption attributes and the inclusion of alternatives, such as WFH, that are not systematically observed in real-world data (Hensher et al., 2005; Rose & Bliemer, 2009). A short RP module collects information on actual experiences with temporary closures to support descriptive analysis and plausibility checks of the SP results. These three survey components are complementary rather than redundant. The attribute-based stated-choice experiment examines how respondents trade off travel time, travel cost, public transport, and working from home under controlled, comparable disruption scenarios. The pivoted experiment complements this by expressing disruption severity relative to each respondent's own commute, enabling analysis of whether adaptation emerges once delays become substantial relative to the usual trip and whether this differs across commuters with different constraints. The revealed-preference module adds a real-world reference point by capturing reported behaviour during experienced disruptions, thereby supporting the interpretation of external validity and the gap between stated intentions and realised responses.

To support the realism of the stated-choice scenarios, two empirical inputs are used. First, an analysis of NDW roadworks records is conducted to characterise when roadworks typically occur (start/end timing, time-of-day patterns and duration). Second, a network impact case study in OMNITRANS is used to translate representative roadwork/closure conditions into additional travel-time impacts. Together, these inputs anchor the disruption-severity attribute levels to observed scheduling patterns and to model-based estimates of travel time penalties.

1.3.4. Data analysis & modelling framework

Survey responses are first subjected to standard data cleaning and descriptive analysis to profile the sample, commuting patterns, and access to alternatives. Behavioural responses in the SP experiments are then modelled using discrete choice techniques. A panel Multinomial Logit (MNL) model provides a transparent baseline. Mixed Logit (MXL) models then allow for random taste variation in key parameters to capture unobserved preference heterogeneity. Finally, a Latent Class specification is explored to identify distinct behavioural segments with different sensitivities to disruption severity (Train, 2008). These model classes are standard tools in transport demand analysis and are well-suited for studying commuters' responses to temporary roadworks (Hensher et al., 2005).

1.4. Relevance

Insight into how people respond to temporary road closures and severe roadworks remains limited, particularly in contexts with widespread hybrid work. Existing studies often focus on single high-profile closures and do not explicitly model WFH as a non-travel alternative. By combining detailed information on disruption severity with a stated-preference experiment that includes working from home as a distinct option, this thesis contributes to the literature on travel behaviour under time-bounded capacity reductions and on the role of WFH in commuting. It also provides empirical evidence from a dense, multimodal Dutch setting, which complements the predominantly North American and UK case studies in the existing literature.

For Sweco, the contribution of this thesis lies not only in improving general understanding of behavioural responses during temporary roadworks, but also in offering a more structured basis for project assumptions and client advice. The findings show that commuter adaptation should not be represented through a single uniform demand-reduction factor, but should instead be interpreted as severity-dependent, shaped by commuter constraints, and communicated as scenario ranges rather than deterministic point estimates. This is directly relevant for project appraisal, traffic and demand modelling, mitigation design, and communication with clients and stakeholders about expected behavioural responses. To support this applied use, Appendix K translates the empirical findings into a concise practical framework for project work, client conversations, and scenario construction.

1.5. Thesis outline

The remainder of this thesis is organised as follows. Chapter 2 reviews the literature on travel behaviour under temporary road disruptions and develops the conceptual framework and survey attributes. Chapter 3 describes the NDW roadworks data and the A4 De Hoek–Burgerveen case study, and derives indicators of disruption severity for the Dutch context. Chapter 4 presents the design of the stated-preference experiments and the online questionnaire. Chapter 5 reports the data cleaning steps and provides descriptive statistics of the sample, commuting patterns, and access to alternatives. Chapter 6 presents the discrete choice model specifications and estimation results for the stated-preference experiments, including analyses of preference heterogeneity. Finally, Chapter 7 summarises the main findings, discusses implications for policy and modelling practice, and provides recommendations and directions for future research.

2
Literature review and conceptual framework

This chapter reviews travel behaviour during planned and unplanned road disruptions. While the review draws on evidence from both planned and unplanned events to identify general behavioural mechanisms, the empirical focus of this thesis is on planned roadworks and pre-announced closures. The objectives are twofold: first, to identify feasible behavioural responses under time-bounded capacity constraints; second, to translate insights from the literature into attributes with clear operational definitions and plausible ranges for the stated-choice experiment. The review synthesises results across disruption types, prioritises studies with commuter samples and revealed and stated-preference designs, and highlights moderators that shape responses. The outcome is a set of design-relevant insights into alternatives, attributes, and levels in the stated-choice components, complemented by a conceptual framework that links disruption characteristics, mode choice, and responses to working from home. While the review covers a broader set of disruption attributes and behavioural responses reported in the literature, the empirical scope and the final selection of alternatives and attributes for the stated-choice design are specified in Chapter 4.

2.1. Search strategy and inclusion criteria

Because this review examines temporary roadworks, associated road closures, and capacity constraints affecting commuters, relevant studies were identified through searches in Scopus and Google Scholar. Keyword queries were formulated to capture cases in which temporary road or lane closures prompted behavioural adaptation, including mode shift and non-travel responses such as working from home. Searches were conducted in October 2025 and were complemented by backward and forward snowball sampling from the most relevant papers. Titles and abstracts were screened for relevance to the scope; studies were included when they concerned disruptions on motorways or other high-capacity roads, focused on commuting or commuter-relevant travel, and reported at least one behavioural response. Full-text access was required for inclusion. Table 2.1 summarises the concept groups and representative keywords; the exact query syntax was adapted to the respective search interfaces.

2.2. Overview of key studies

Table 2.2 summarises key studies, indicating for each reference the focus area, disruption type, methodological approach, and location. Research on behavioural responses to road closures and capacity restrictions is a relatively recent strand in the assembled literature. Early contributions date to the early 2000s, followed by a more pronounced increase from around 2010 onward. The evidence base is geographically skewed towards North America—particularly Sacramento, Los Angeles and Minneapolis—with selected European cases and a small number of Asian examples. By disruption type, bridge and freeway closures dominate, whereas tunnel and lane-specific closures are analysed less frequently. A small number of studies address congestion conditions or mega-events rather than discrete closures;

Table 2.1: Search queries

Concept groups	temporary road closure; lane closure; roadworks; work zone; commuter travel behaviour
Keywords	temporary road closure; lane closure; work zone; roadworks; detour; reroute; route diversion; telework; work from home; non-travel; trip cancellation
Truncation	("work zone*" OR "roadworks" OR "lane closure" OR "temporary road closure") AND ("telework*" OR "work from home" OR "non-travel" OR "not travel")

these are retained only when they report behavioural responses relevant to commuter adaptation mechanisms.

2.2.1. Methods in disruption studies

The literature on responses to temporary road closures uses a wide range of empirical methods, reflecting the diversity of disruption types and contexts. Most studies use revealed-preference (RP) surveys to record what people actually did during or right after a closure. Other research uses stated-preference (SP) experiments to test hypothetical choices under controlled conditions. Some studies combine both survey types. A few research papers rely on passive data, such as traffic sensors, GPS, or loop detector data, to examine changes in travel behaviour. Others combine survey results with overall traffic counts and public transit ridership data. Together, these approaches provide complementary evidence on how commuters adapt during disruptions in both planned and unplanned settings.

RP studies are common because real closures function as natural experiments and provide evidence of behaviour under real-world conditions. Typical studies use short questionnaires administered to people living near the corridor or to on-site commuters, and they verify responses against administrative or sensor data. Well-known cases are the Sacramento Fix-I-5 freeway closure and the I-35W bridge failure in Minneapolis (Ye et al., 2012; Yun et al., 2011; Zhu et al., 2010). UK bridge closures show similar adjustments for commuting and non-commuting travel, often confirmed by local traffic data (Guiver, 2011; Shires et al., 2016). Where available, connected-vehicle or diary data help to separate detours from foregone trips (Desai et al., 2022).

RP is strong on realism, but it also has limits. Results depend on one specific site, its detour options, the information provided to travellers and the season. Key attributes, such as closure duration, time of day, and additional travel time, cannot be varied independently, making outcomes highly case-specific and limiting their direct transferability to ex ante planning in other settings. Recall bias grows if surveys are administered long after the event. Most RP work is event-centred and therefore provides rich descriptions of behavioural "bundles" during a particular closure, but offers fewer clearly identified behavioural parameters for strategic planning (Guiver, 2011; Shires et al., 2016; Ye et al., 2012; Yun et al., 2011).

Stated-preference designs complement RP by controlling the choice context and systematically varying disruption attributes, thereby enabling the identification of attribute trade-offs that RP cannot cleanly separate. Although SP is used more often in congestion and pricing contexts than in short closure settings, it has proven effective for testing commuters' willingness to retime, reroute, switch mode, or adopt non-travel responses when confronted with explicit changes in travel time and reliability (Albert & Mahalel, 2006). Related work on peak-avoidance incentives and information effects illustrates how SP can isolate behavioural mechanisms that are difficult to observe in the field (Avineri & Prashker, 2006; Bamberg et al., 2003; Ben-Elia et al., 2010, 2011). For this thesis, SP is therefore a suitable tool to operationalise additional travel time relative to a commuter's baseline and to test whether responses differ by disruption timing, while holding other contextual elements constant. Timing within the day matters because baseline congestion, schedule constraints (especially during the morning commute), and substitute performance (public transport frequency and crowding) differ systematically across peak periods. As a result, otherwise identical increases in travel time can imply different behavioural trade-

Citation	Focus area	Disruption	Methodology	Location
Albert and Mahalel (2006)	Congestion tolls, parking fees and travel behaviour	Congestion	Stated preference survey	—
Brown et al. (2017)	Public response to highway closures	Highway closure	Travel data	Los Angeles
Danczyk et al. (2017)	Expected vs. unexpected disruption effects on travel	Bridge disruption	Literature review	Minneapolis
Fujii and Gärling (2003)	Modal shift during an eight-day bridge closure	Bridge closure	Revealed preference	Osaka
Guiver (2011)	Travel adjustments after a road closure	Road closure	Revealed preference	Workington
Hunt et al. (2002)	Responses to the Centre Street Bridge closure	Bridge closure	Not reported	Calgary
Desai et al. (2022)	Route choice during (un)planned road closures	(Un)planned road closures	Connected-vehicle data	Chicago
Kemmerer et al. (2023)	Risk perception and mode choice during a temporary closure	Freeway/ bridge closure	Revealed preference	Wiesbaden/Mainz
Calvert and Melia (2023)	Disappearing traffic in a strategic bridge closure	Strategic bridge closure	Traffic-sensor data	Bristol
Parkes et al. (2016)	Travel behaviour change during mega-events	Congestion (mega-event)	Longitudinal survey	London
Shires et al. (2016)	Commuting changes during the Forth Road Bridge closure	Bridge closure	Revealed preference	Queensferry
Timmins and Murdock (2007)	Congestion measurement in travel cost models	Congestion	Revealed preference	Wisconsin
Tympakianaki et al. (2018)	Network disruption impacts using multimodal data	Tunnel closure	Sensors	Stockholm
Ye et al. (2012)	Commuter impacts of a temporary freeway closure	Freeway closure	Revealed preference	Sacramento
Yun et al. (2011)	Non-work travel changes during the Fix I-5 freeway closure	Freeway closure	Revealed preference	Sacramento
Zhu and Levinson (2008)	Review of planned and unplanned network disruptions	(Un)planned road closures	Literature review	—
Zhu et al. (2010)	Traffic and behavioural effects of the I-35W bridge	Bridge closure	Loop detectors	Minneapolis

Table 2.2: Studies on road or capacity disruptions and behavioural responses.

offs depending on whether the disruption affects the outward (morning) or return (evening) commute.

A third stream uses loop detectors, GPS, and multimodal sensors to infer diversion patterns and net demand loss during closures, sometimes referred to as ”disappearing traffic” or ”evaporation” because traffic is not observed on alternative routes around the disruption (Tympakianaki et al., 2018; Zhu et al., 2010). These sources excel at high-frequency exposure and recovery dynamics and at distinguishing rerouting from volume suppression, but they generally cannot tell why travellers changed without survey augmentation. Hybrid designs that combine RP/SP with sensors or connected-vehicle data are therefore the most informative for planning (Calvert & Melia, 2023; Desai et al., 2022).

2.3. Travel behaviour responses to temporary road disruptions

2.3.1. Behavioural options during disruptions

Table 2.3 summarises which behavioural responses each study analysed during different disruptions. An 'X' indicates that the response was measured or used in some way. The blank cells indicate that the response was not reported. The response categories are rerouting (same mode, different path), retiming (shifting departure or arrival time), mode shift, trip suppression (cancelling or postponing the trip), and telework (replacing the commute with telework). Taken together, the reviewed cases show that rerouting and retiming are most frequently captured and often account for a large share of observed adjustments, whereas mode shift and non-travel responses are less consistently measured and typically reported at lower rates. These patterns motivate this thesis's focus on the relative roles of continuing by car, switching to public transport, and working from home during planned disruptions, while recognising that intramodal adaptations are reflected indirectly through realised changes in travel time.

Citation	Reroute	Retiming	Mode shift	Trip suppression	Telework
Brown et al. (2017)	X		X	X	
Danczyk et al. (2017)	X				
Fujii and Gärling (2003)			X		
Guiver (2011)	X		X	X	
Hunt et al. (2002)	X				
Desai et al. (2022)	X				
Kemmerer et al. (2023)	X		X		
Calvert and Melia (2023)	X				
Parkes et al. (2016)	X	X	X	X	X
Shires et al. (2016)	X	X	X	X	X
Tympakianaki et al. (2018)	X		X		
Ye et al. (2012)	X	X	X		X
Yun et al. (2011)	X	X	X	X	
Zhang et al. (2012)	X	X	X		
Zhu et al. (2010)	X	X	X		

Table 2.3: Options during disruptions per paper

2.3.2. Intramodal adaptations: rerouting and retiming

Rerouting

Changing the route is a very common response, especially when a road is physically closed. The collapse of the I-35W bridge in Minneapolis is a key case of an unplanned disruption (Desai et al., 2022; Zhu et al., 2010). A revealed preference survey by Zhu et al. (2010) found that 51.1% of travellers changed their route on the day after the collapse. This number remained high, with 46.1% still using an alternative route by the end of September. This suggests that many drivers were forced to reroute and that a substantial share continued to use alternative routes over time. This was a sudden, unplanned event.

The response may differ for planned closures. The 'Fix I-5' project in Sacramento was a planned freeway repair (Zhang et al., 2012). Here, researchers found a slight reduction in freeway demand during the peak period, by only 7% to 12%. This was explained by the fact that most drivers who avoided the freeway did so by using arterial routes (rerouting) or by changing their departure time (retiming). Other studies on the same event confirm that rerouting was a common strategy for both commuter trips and non-work trips, with a 44% rate (Ye et al., 2012; Yun et al., 2011). The rerouting percentage is slightly lower than in the I-35W case. This difference may reflect contextual factors: the I-5 works were planned, which may have facilitated advance adjustments (rescheduling or working from home), and the corridor offered more parallel routes, whereas I-35W involved a single bridge link with fewer close substitutes (Zhu et al., 2010).

Newer methods show similar findings. Desai et al. (2022) used Connected Vehicle data from Chicago. For total road closures lasting more than five hours, they observed very high diversion rates, ranging from 58% to 93%. These numbers appear much larger, but they measure the flow of vehicles that must be diverted from a specific link. The survey data from Zhu et al. (2010) measure the percentage of people in the corridor who reported changing their usual trip. Both methods support the conclusion that rerouting is a primary and immediate response to a complete closure.

Retiming

The second major option is retiming, also known as 'peak spreading'. This is when travellers leave earlier or later to avoid congestion. The I-35W bridge collapse gives an interesting insight (Zhu et al., 2010). On the day after the collapse, 27.7% of travellers changed their departure time. This number then increased to 31.9% over the following weeks before stabilising at 29.8%. The growth of retiming suggests that it may have emerged as a secondary response relative to rerouting. Following the bridge collapse, many travellers rerouted, while departure times changed significantly over the subsequent period (Zhu et al., 2010). One possible explanation is that congestion on detour routes made retiming more attractive for part of the affected population. Retiming can thus also be a response to the problems caused by rerouting.

The situation is different for planned, network-wide congestion. The London 2012 Olympics is a good example of a big event where authorities warned travellers to expect congestion (Parkes et al., 2016). The study of Parkes et al. (2016) found that retiming (25%) was the more common response, while rerouting (16%) was less common. This contrast suggests that the type of disruption matters. For unplanned closures, rerouting may be more necessary because network connectivity is disrupted. For a planned congestion event, all routes are open but busy, so retiming may be a more attractive strategy.

This 'peak spreading' was also seen in the planned 'Fix I-5' project. This behaviour can also be encouraged by policy. Studies in the Netherlands on the 'Spitsmijden' (peak avoidance) project found that giving rewards was effective in discouraging peak driving (Ben-Elia et al., 2010, 2011).

These intramodal adaptations (rerouting and retiming) have a limit. The closure of the Forth Road Bridge in Scotland is a case study that illustrates this limit (Shires et al., 2016). This was a severe, unplanned closure of a major bridge. However, the only available detour imposed a very high generalised cost, roughly doubling journey times and adding around 90 minutes. In this setting, intramodal adjustment became less attractive, and the evidence points to a substantially larger shift to rail alongside a reduction in commuting days, consistent with teleworking.

In this situation, rerouting was not the main response. The detour was too long and costly for most commuters. Instead, the literature points to a substantial shift in intermodal transport. Shires et al. (2016) found that around 60% of car users switched to rail. The same study also found a 12% reduction in the number of days people travelled to work, suggesting teleworking. This case illustrates a boundary condition. Rerouting remains attractive only if the alternative route is still tolerable. When the cost of rerouting becomes too high, travellers may be more likely to switch modes or reduce commuting.

2.3.3. Intermodal adaptations: mode shift

Modal shifts, when commuters switch from driving to public transport, cycling, or walking, typically require a significant change in conditions. The literature often frames reducing car dependence as an important objective for sustainable transport, but the specific triggers for modal shifts are complex and context dependent (Meinherz, 2020). In practice, shifts tend to occur only when alternatives become clearly more attractive or when car travel becomes less convenient or more costly.

Changes in cost and pricing trigger a modal shift. Increasing the monetary or time cost of driving, via fuel taxes, congestion charges, tolls, or expensive parking, raises the relative utility of public transport and cycling. Evidence on cross-elasticity indicates a reallocation from car to public transport when driving costs rise (Fearnley, 2016). A Dutch example corroborates this. A hospital's parking price increase combined with a kilometre allowance reduced car commuting from 45% to 20% (EPOMM, 2011). Employer programmes (mobility budgets, PT passes, secure bike parking) further tip choices at the margin (Heinen et al., 2012; Shoup, 1997; Yang et al., 2015).

Major life or job changes are also widely recognised triggers: moving house, changing jobs, retirement, or childbirth disrupt established routines and prompt reconsideration of mode choice. Evidence from London indicates that more than half of observed changes in travel behaviour were attributable to external events (Rahman, 2023). Dutch panel data likewise indicate that moving home or starting a new job is associated with switching (often toward cycling when commutes shorten). In contrast, childbirth or a longer commute can discourage it (Oakil et al., 2014).

Capacity constraints limit the extent to which modal shifts can occur in practice. Public transport frequency and crowding may cap the number of additional riders that can be accommodated, so residual demand is often absorbed by intramodal rerouting or retiming rather than by large-scale intermodal switching.

Mode shift during temporary road closures

As evidenced by numerous cases, modal shift tends to occur only under certain conditions. These conditions are that the increase in car travel time or difficulty must be substantial enough to outweigh the benefits of the preferred mode, and the alternative must be sufficiently attractive and accessible to accommodate those who are shifting. In roadworks contexts, perceived reliability degradation (greater travel-time variability) is often as consequential as mean delay. Minor increases in congestion typically result in route or time adjustments rather than large-scale mode switching. However, in severe scenarios, such as a major bridge closure that doubles commute times, noticeable modal shifts can be observed.

Kemmerer et al. (2023) surveyed an unexpected two-month closure of a major Rhine River bridge and found that 22% of car commuters switched to alternative modes during the closure. The reported share indicates a substantial impact for that specific closure. Given the short disruption horizon and the critical detour congestion, generalisation to routine works requires caution. The closed bridge was a critical link, and the detour routes were very congested. This resulted in nearly a quarter of drivers temporarily abandoning driving. Their analysis reveals that individuals who changed alternative modes during the closure often cited specific motivations, including health risks associated with air pollution. In other words, those who viewed car travel as harmful were more likely to change their behaviour. This suggests that attitudinal factors can play a role when the context forces a decision.

Fujii and Gärling (2003) examined an eight-day closure in Osaka and found a smaller modal shift toward public transport, measured as a percentage. However, an interesting finding was that among those who did shift, many updated their perception of public transport positively. After the freeway reopened, some of these travellers did not immediately resume full-time driving. During the closure, some travellers learned that the train was acceptable, while others continued to use public transport at least occasionally. This indicates that intermodal switching can persist among a subset of travellers when positive experiences outweigh the return to normal car conditions. However, maintaining a modal shift requires that the alternative remain competitive. In Osaka, once the freeway was reopened and congestion returned to normal, only those who had found public transport genuinely convenient or had developed a strong pro-public transport attitude continued to use it. Many others reverted to old habits.

In 2008, part of Interstate 5 near Sacramento, California, was closed in one direction during commuting hours. Zhang et al. (2012) examined whether new public transport riders would keep riding after the freeway reopened. They concluded that there was evidence of peak spreading rather than a sustained shift to public transport, and that the majority of drivers selected alternative departure times or routes, then returned to their routine after the works were completed. In other words, intra-modal retiming dominated intermodal switching.

Therefore, there are different behaviours and types of modal shift. A temporary shift in which people change mode during the disruption and revert afterwards. Secondly, a sustained shift in which the mode change persists even after normal conditions return. Temporary shifts are far more common. Sustained shifts occur in a minority of cases, typically when people actually find the new mode superior or when something else changes in their lives. The habit discontinuity hypothesis posits that a context change opens a window for behaviour change, but whether that change sticks depends on reinforcing factors (Aarts et al., 1997). If, during that window, the traveller forms a new habit, they may not resume driving. If they found the new mode only tolerable as a necessity, they would revert as soon as possible.

In conclusion, modal shift under temporary road closures is typically limited but non-negligible. The first responses are usually not modal, but as delays persist or worsen, more drivers explore other modes or refrain from travelling. Across major link closures and high-impact works, reported inter-modal shifts are generally in the single-digit to low two-digit range during disruptions, with higher figures in critical-link cases. These findings support the inclusion of a public transport alternative in the stated-preference design, but also caution against assuming large intermodal shifts under temporary closures.

2.3.4. Non-travel responses: trip cancellation and telework

Non-travel responses, including working from home and trip suppression, are often underappreciated in disruption analyses because they are less directly observable than rerouting or retiming. In this thesis, the non-travel response is operationalised as working from home within the stated-choice design, reflecting a workday framing in which respondents are assumed to be working. The literature suggests that telework uptake during specific disruption events is often reported in the single digits, although rates depend strongly on job feasibility, employer policies, and the advance notice associated with planned work. In a post-COVID context with widespread hybrid arrangements, the potential contribution of working from home to demand reduction during planned disruptions is an important mechanism to explicitly represent.

Disappearing traffic and telework

Disappearing traffic, also known as traffic evaporation, refers to the empirically observed reduction in motor-vehicle volumes that follows declines in road capacity. In contrast to simple diversion, some trips are no longer observed anywhere in the monitored network after implementation. The classic syntheses report that, across diverse cases, overall motor traffic often falls rather than being entirely displaced, with a typical median of around 11% in treated areas (Cairns et al., 2001). Interpretation depends on the scope and design of the measurement. Conceptually, evaporation is the mirror image of induced demand: when generalised costs of car travel rise and viable substitutes exist, part of the previously induced traffic does not materialise.

The size and persistence of evaporation effects vary systematically with the intervention's network role, the quality and availability of substitutes, and the presence or absence of spare capacity on adjacent routes. In their synthesis of more than seventy international schemes, Cairns et al. (2001) report that reallocations, such as pedestrianisation, bus priority, or lane removals, tended not to produce the widespread gridlock predicted. Persistence is higher when interventions affect critical links and are sustained or accompanied by complementary measures. Short, isolated restrictions more often lead to temporary evaporation.

There are multiple behavioural responses broader than simple route choice that explain the observed outcomes. Cairns et al. (2001) report multiple mechanisms that can explain traffic evaporation, such as modal substitution, trip combining and retiming. Additional mechanisms include trip suppression, teleworking, and destination substitution, which reduce observed volumes without necessitating a one-for-one increase elsewhere.

A recent Dutch stated-preference study adds further nuance to these findings in the context of commuting (van Dijk, 2022). van Dijk (2022) surveyed 414 car users living in larger Dutch cities and presented them with scenarios in which car travel times were increased by 5–20 minutes, or the walking time to their parked car was extended. For work and study trips, even a modest five-minute increase in in-car travel time led to an estimated 7.2% of trips "disappearing", in the sense that respondents reported either switching mode or not making the trip at all; at +20 minutes this rose to 32.5%. In more realistic 5–10-minute extensions, van Dijk concludes that approximately 10% of car trips could be avoided. Disaggregated by response type, the study shows that, especially for work and study trips, more respondents reported they would not make the trip than that they would switch modes, indicating that trip suppression (including teleworking) is at least as important as intermodal substitution for commuters.

In the report on the emergency closure of the Forth Road Bridge, Shires et al. (2016) found a 12% reduction in the number of days people travelled to work during the closure. This 12% reduction was a combination of different behaviours. The same report noted that 11% of respondents cancelled trips.

Out of the 11%, three-quarters were offset by home working (Shires et al., 2016). This clearly shows that trip cancellation and teleworking are distinct, measurable responses that together account for the total "disappeared" traffic. The study of the planned Fix I-5 freeway closure in Sacramento found that 5.6% of the total eligible respondents increased telecommuting because of the closure (Ye et al., 2012).

Teleworking is an increasingly important alternative to travel. Individuals tend to telework when their job tasks can be performed remotely, particularly when commuting costs or difficulties are high (Chalabi & Dia, 2024). In general, high-skilled, office-based occupations with flexible schedules are most amenable to telework. For these workers, longer commutes, high wages and job flexibility make working from home attractive (Chalabi & Dia, 2024).

Employer policies and workplace culture strongly influence teleworking. Some workplaces actively support remote work, thereby significantly increasing uptake. Conversely, if an employer forbids remote work or lacks trust in off-site productivity, teleworking is difficult (De Graaff, 2004). Organisational constraints, such as the need for face-to-face collaboration, data security rules, or simply company policy, can prevent telework even when the job would allow it.

The COVID-19 pandemic led to a dramatic, if temporary, rise in teleworking that is expected to have lasting effects. Health concerns and restrictions forced many employers and workers to discover that remote work was feasible and often effective (Adobati & Debernardi, 2022; Athanasiadou & Theriou, 2021). This has created a "new normal" in which telework is a persistent part of commuting patterns (Ashour & Shen, 2025). Post-pandemic surveys found higher overall adoption of home working than before, with many workers telecommuting more days per week (Chalabi & Dia, 2024). Reflecting this trend, researchers predict that a sizeable share of workers will keep hybrid or full-time telework arrangements long after COVID restrictions end because employees and employers are now familiar with the technology, the workflows, and the policies for remote work (Athanasiadou & Theriou, 2021).

In modelling temporary scenarios, one pragmatic approach is to treat telework or non-travel as a special mode that absorbs a certain percentage of trips when travel times become extreme. Some activity-based models do this by having persons decide to cancel tours if the impedance is too high. A more straightforward approach in scenario planning is to reduce the trip matrix by a specified percentage to represent the avoided trips. Cairns et al. (2001) reported around 11% average "disappearing traffic" following capacity reductions. This estimate is from a pre-COVID context, dating back to 2001. Given the wider prevalence of hybrid work in the post-COVID period, non-travel responses may be more plausible under disruptive conditions than in the pre-COVID cases summarised by Cairns et al. (2001). If non-travel responses are ignored, scenario-based impact assessments may overestimate traffic volumes and resulting congestion on the remaining network.

On the other hand, one must also be cautious about assuming a shift to cycling or public transport is too high. Capacity constraints and traveller resistance can limit these options. Public transport capacity can be a binding constraint. If a commuter rail line is already full during peak hours, it cannot accommodate twice its usual load because a highway is closed. In such cases, only a limited number of drivers can shift to public transport, and the rest will either adjust their schedules or endure the traffic. Some studies explicitly note that crowding during a strike or closure can deter people from using public transport, even if they want to (Tympakianaki et al., 2018).

2.3.5. Conclusion

This review has synthesised empirical and conceptual work on how travellers respond to road closures and capacity restrictions, with a focus on commuting. A limited set of high-impact bridge and freeway closures dominates the evidence base. Most studies examine unplanned or emergency events, such as sudden bridge failures or unexpected closures, while planned works and network-wide congestion events are less frequently analysed. Tunnel and lane-specific closures appear only sporadically. Methodologically, revealed-preference surveys around specific events and passive traffic data provide the backbone of the literature, complemented by a smaller strand of stated-preference experiments and hybrid designs that combine survey and sensor data.

Across these cases, a consistent behavioural ordering emerges. When car travel remains feasible, and detours are tolerable, intramodal adaptations, such as rerouting and retiming, account for the largest share of the response. A substantial fraction of commuters changed their routes or departure times. At the same time, only small minorities switched to other modes or chose not to travel (Ye et al., 2012; Yun et al., 2011; Zhu et al., 2010). Planned congestion events, such as the London 2012 Olympic Games, confirm this pattern, in which many commuters altered their timing or route, whereas intermodal shifts remained more limited (Parkes et al., 2016). Severe cases where detours impose considerable additional travel times, mark the boundary of this pattern and show larger shifts to rail and noticeable reductions in the number of commuting days (Kemmerer et al., 2023; Shires et al., 2016). Overall, reported intermodal shifts during temporary closures are often in the single-digit to low two-digit range in the reviewed cases, with higher figures in critical-link settings. This supports including a public transport alternative in the stated-preference design, while cautioning against assuming large intermodal shifts as a default response to temporary closures.

Non-travel responses, including teleworking and cancelling or postponing trips, are less frequently measured but form an essential part of the picture. Event-specific studies report that only a small share of commuters explicitly increase teleworking or cancel trips during closures, typically in the single digits (Shires et al., 2016; Ye et al., 2012). At the same time, syntheses of disappearing traffic with median reductions around 11% are reported in treated areas (Cairns et al., 2001). This suggests that non-travel and destination substitution contribute meaningfully to observed volume changes, even when they are not directly observed in standard data sources. Most of this evidence comes from pre-COVID contexts in which telework was less institutionalised than today.

Recent Dutch work on disappearing traffic reinforces this picture and sharpens its relevance for commuters. Using a stated-preference survey among urban car users, van Dijk (2022) finds that relatively small increases in car travel time (around five to ten minutes) already lead to the disappearance of roughly 10% of trips, with higher values for more extreme delays. For work and study trips in particular, respondents were more likely to forgo the trip altogether than to switch modes, suggesting that trip suppression and telework may predominate over modal shifts when commuting becomes substantially more burdensome. In a post-COVID context, where hybrid working is technically and institutionally feasible for many white-collar jobs, these findings imply that non-travel responses could be even more important under temporary closures than earlier international case studies suggest.

2.3.6. Discussion

This synthesis clarifies the primary mechanisms by which commuters respond to temporary road closures and also reveals several gaps that motivate the present thesis. A first gap concerns the role of disruption severity and its temporal context. In event-specific revealed-preference evidence, observed delays are strongly conditioned by the time of day (and the commute leg) at which the disruption occurs, making it difficult to disentangle additional travel time from the peak-period context in which it materialises. As a result, it remains challenging to identify how additional travel time and disruption timing jointly reorder the probabilities of continuing by car, switching mode, or adopting non-travel responses.

A second gap is the underestimation of non-travel responses in the structural model. Traffic counts, sensor data and many RP surveys observe realised trips, not deliberate decisions to stay at home. As a consequence, teleworking, cancellation and substantial schedule changes are often inferred indirectly, or not captured at all, even though they help to explain observed ”disappearing traffic” (Cairns et al., 2001). Post-pandemic work practices increase the plausibility that such non-travel responses are both more common and more responsive to the severity of disruption. Yet, little quantitative evidence exists for time-bounded closures in commuter settings.

Third, the empirical base is heavily skewed toward a limited set of North American and UK case studies, often centred on strategic bridge links in car-oriented regions. There is relatively little evidence for dense, multimodal urban regions with high baseline public transport supply and widespread hybrid working arrangements, as in the Dutch context. Moreover, most sources predate the COVID-19 pandemic and therefore reflect a different institutional and cultural environment for telework.

Together, these gaps justify the research design adopted in this thesis. By treating disruption severity as a joint construct of additional travel time and the timing of the disruption (time of day), and by including non-travel (working from home) as an explicit alternative alongside continuing by car and switching to public transport, the stated-preference components directly target the missing behavioural parameters identified in the literature. The survey is anchored in commuters’ own baseline trips and organisational context, enabling estimation of how disruption severity reshapes the probabilities of continuing by car, changing mode, or working from home in a setting comparable to dense Dutch urban regions.

2.4. Conceptual framework

This section presents the conceptual framework that brings together the main mechanisms identified in the literature on travel behaviour during temporary road disruptions. Temporary roadworks, lane closures, and other capacity-reducing events do not merely add a few minutes of delay to otherwise stable commuting patterns. They may disrupt habitual routines, alter perceived risks across options, and confront travellers with the question of whether to continue commuting as usual, adjust their trip, or avoid travel altogether. The framework summarises how the characteristics of disruption, individual and household contexts, work arrangements, and accessibility conditions jointly shape these responses. It is based on the reviewed empirical and theoretical studies on roadworks, closures and related disruptions. It is intended to provide structure for the variables that will later be operationalised in the empirical analysis. It is important to note that this framework does not aim to list every possible factor influencing travel behaviour exhaustively. Instead, it identifies the key determinants identified in previous empirical studies on road closures and capacity reductions. Subsequently, it justifies which of these are retained within the specific scope of this thesis.

2.4.1. Alternative behavioural responses

The literature on temporary disruptions consistently shows that travellers have several options when faced with disruptions on the road. When faced with severe roadworks or closures, commuters may reroute within the same mode, shift their departure time, switch to public transport or active modes, change destination, reschedule activities, work from home, or cancel trips altogether (Fujii & Gärling, 2003; Ye et al., 2012; Zhu et al., 2010). These responses can be grouped into three broad categories.

First, there are *intramodal adjustments*, in which commuters remain in the same primary mode but adapt their use of it. This includes choosing an alternative route, accepting a longer detour, adjusting departure time to avoid the peak of the disruption, or combining them (Ye et al., 2012; Zhu et al., 2010).

Second, there are *intermodal shifts*. Some commuters switch from driving to public transport or, less frequently, to cycling or walking, depending on the availability and quality of alternatives. Several case studies report non-trivial increases in public transport ridership during closures, especially where rail or high-quality bus services provide a reasonably competitive alternative to the disrupted car route (Fujii & Gärling, 2003; Kemmerer et al., 2023).

Third, there are *activity-based responses*, where the trip itself is modified or suppressed. Travellers may change destination, combine trips, postpone activities, or decide not to travel. In the context of commuting, teleworking has emerged as an important non-travel response. Recent studies indicate that, for work trips, a substantial part of the apparent disappearing traffic during disruptions is in fact due to telework or trip cancellation, rather than pure rerouting within the network (Shires et al., 2016; van Dijk, 2022).

2.4.2. Attributes

Empirical studies on temporary road disruptions are reviewed to identify which attributes are used to represent travellers' choices. Rather than treating travel time and cost as sufficient statistics, most disruption studies enrich the utility specification with attributes that capture reliability, temporal constraints, information and work-related flexibility.

Table 2.4 summarises the main attributes that appear across a set of frequently cited disruption studies. For each paper, it indicates whether the authors explicitly include attributes of travel time or delay, monetary costs, the reliability or variability of travel time, the duration of the disruption, information and awareness, and telework or work flexibility. A check mark in parentheses denotes attributes that are not specified directly in the paper itself but are used as contextual variables or are in the discussion that would have enriched the research.

Across all reviewed studies, some clear patterns emerge. Travel time or delay is present in every case, confirming its central role as the primary impediment in disruption settings. Depending on the context, it is specified as total journey time, as separate components, or as an additional delay relative to

Table 2.4: Attributes in reviewed studies on travel behaviour during temporary road disruptions.

Reference	Travel time / delay	Travel cost	Reliability	Duration of disruption	Information	Telework / work flexibility
Ye et al. (2012)	✓	(✓)			✓	✓
Shires et al. (2016)	✓	(✓)		✓		✓
Albert & Mahalel (2006)	✓	✓				
Zhu et al. (2010)	✓					
van Dijk (2022)	✓	✓				(✓)
Parkes et al. (2016)	✓			✓	✓	✓
Tympakianaki et al. (2018)	✓		✓			
Yun et al. (2011)	✓				✓	

usual conditions. Monetary cost appears in many, but not all, studies. In several revealed-preference applications, it is only implicit, being derived from distance or existing tolls rather than being varied experimentally.

A second group of attributes captures various forms of uncertainty and temporal constraints. Some studies introduce explicit measures of travel time variability and show that commuters are strongly risk-averse: higher travel time variance reduces the attractiveness of a route even when the mean time remains unchanged.

Information-related attributes are reported in studies evaluating large-scale planned events or high-profile closure projects. Here, indicators such as awareness of the disruption, use of travel information sources, and exposure to information campaigns help explain why some commuters adjust their departure times, routes, or modes, while others do not.

Finally, more recent work explicitly considers telework and work flexibility. Earlier disruption studies often inferred ”disappearing traffic” indirectly from observed volume changes, without modelling telework as a distinct behavioural option. Subsequent studies began to include indicators of job flexibility, employer permission to work from home, and actual telework use. These variables are typically treated as contextual or constraint attributes that condition whether a non-travel response is feasible when disruption severity increases.

Overall, the literature suggests that travel time and cost remain the backbone of utility specifications, but that reliability, duration, information and work-related flexibility are crucial additional dimensions in disruption settings. Together, these attributes describe not only how burdensome a disrupted trip is, but also how much room travellers have to adapt.

2.4.3. Sociodemographics/background variables

The sociodemographic and background variables influencing travellers’ choices during temporary road disruptions are derived from the reviewed literature on road closures, capacity reductions, and general travel behaviour. These characteristics do not determine behaviour directly but shape the constraints, opportunities and preferences that underpin individuals’ utility evaluations. Factors such as age, income, and education influence access to transport resources, sensitivity to travel time or cost, and the feasibility of switching to alternative modes of travel. Household composition and car ownership determine whether travellers have access to a private vehicle or must rely on public transport or active modes.

In addition to individual and household characteristics, work and organisational context variables further constrain the set of feasible responses. Factors such as the ability and habit of teleworking, flexibility in working hours, requirements for physical presence, and employer policies determine whether non-travel responses are realistically available as disruption severity increases. These elements are grouped in the ”work & organisational context” box in Figure 2.1.

In addition, several background variables reflect the broader mobility context within which disruption responses occur. Bicycle or e-bike ownership increases the feasibility of switching to active modes when car travel becomes less attractive. Similarly, holding a driving licence affects whether car-based responses, such as continuing by car or rerouting, are feasible alternatives. As highlighted in recent disruption studies, previous experience with roadworks and familiarity with travel information sources can also condition how travellers perceive disruption severity and the credibility of information provided. These background factors jointly help explain heterogeneity in behavioural responses and provide structure for the variables later used in the empirical analysis.

2.4.4. Trip and disruption characteristics

Disruption characteristics, such as additional travel time caused by roadworks, the timing of the disruption (time of day), its predictability, and the extent of the closure, are expected to affect whether travellers continue commuting as usual, adjust their trips, or refrain from travelling altogether. For commuting, timing within the day is particularly relevant because morning trips typically face tighter arrival-time constraints, whereas the return commute often allows more temporal flexibility. Moreover, the performance and capacity of substitutes (public transport frequency, crowding, and cycling conditions) vary across peak periods, which can make responses asymmetric between the outward and return trips.

Trip-related factors determine which alternatives are realistically available to the traveller. Trip purpose strongly affects the degree of temporal flexibility, with work-related trips often being more time-constrained than leisure or discretionary travel. Trip distance and route familiarity influence the feasibility of rerouting or switching to active modes. Whether the trip is outbound or return can also shape behavioural options. Together, these trip and disruption characteristics interact with individual, work-related and perceptual factors to determine the utility of different behavioural responses during temporary roadworks.

A final set of determinants relates to the accessibility and performance of alternatives during the disruption. Travel time and reliability of public transport, expected crowding, the feasibility of cycling or walking, carpool availability, and the practical possibility of shifting departure time jointly determine whether alternative options are perceived as realistic substitutes for the disrupted car trip. In the conceptual framework, these factors are grouped in the ”Accessibility and performance of alternatives during disruption” box.

2.4.5. The full conceptual framework

Figure 2.1 presents the full conceptual framework developed for this thesis. The framework synthesises the key mechanisms identified in the literature on travel behaviour during temporary road disruptions. Rather than viewing roadworks as simply an increase in travel time, previous studies emphasise that disruptions alter habitual routines, introduce uncertainty, and trigger a range of behavioural adjustments. These responses depend not only on the characteristics of the disruption itself but also on individual, household, work-related, and contextual factors that shape travellers’ constraints and opportunities.

At the top of the framework, the dashed boxes represent the determinant categories that influence the utility of different behavioural responses. Each of these groups contains factors that the literature has shown to affect travellers’ sensitivity to delay, their ability to switch modes, reschedule activities or work from home, and their reliance on information and previous experience.

All determinant groups feed into the central latent construct, labelled Utility. This reflects the idea that travellers evaluate the attractiveness of each possible response based on perceived travel burden, flexibility, comfort, reliability and feasibility. Although utility is not directly observable, it integrates the effects of all relevant factors and underpins the behavioural choices made during a disruption. Importantly, the framework shown in Figure 2.1 represents the complete conceptual model: all elements highlighted in green are explicitly operationalised and taken forward in the empirical design and analysis of this thesis.

The bottom part of the framework displays the set of possible behavioural responses, grouped into three broad categories. Modify trip captures intramodal adjustments, such as rerouting, retiming, carpooling, or reducing trip frequency. Mode shift refers to the shift from private transport to public transport, cycling, or walking. Finally, replacing or cancelling a trip constitutes an activity-based response, such as teleworking or choosing a different destination. Together, these pathways summarise the behavioural flexibility documented in empirical studies on roadworks and temporary capacity reductions. Not all of these responses are, however, represented as separate alternatives in the empirical design of this thesis.

The framework provides the conceptual structure for the empirical analysis in subsequent chapters. It clarifies how different determinants interact and which behavioural avenues are theoretically plausible, without yet imposing specific modelling assumptions. The attributes and variables selected for the stated choice and pivoted components of the survey are grounded in this overarching structure, with all green-highlighted components directly informing the survey operationalisation and subsequent modelling.

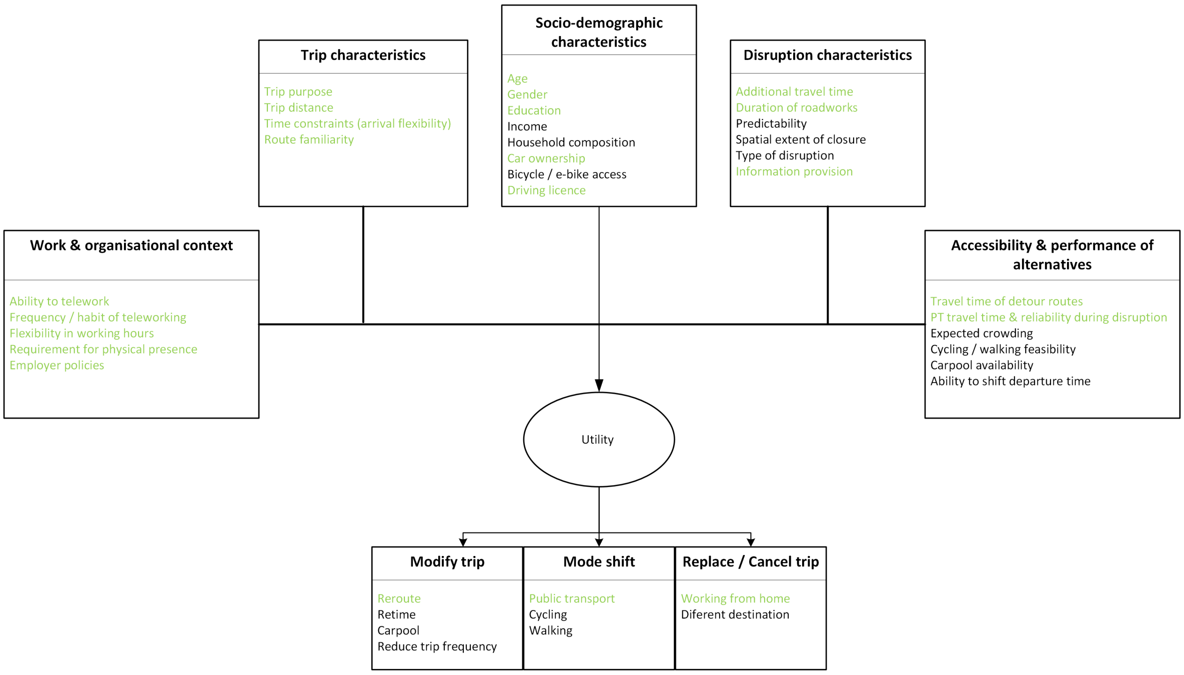


Figure 2.1: Full conceptual framework for behavioural responses during temporary roadworks. The boxes represent the determinants of the perceived utility of different responses. The central utility construct integrates these influences, yielding the set of possible behavioural adjustments shown at the bottom of the figure. Green-highlighted elements indicate components that are operationalised and included in the empirical analysis in this thesis.

3 Roadworks data and network impact case study

This chapter empirically characterises the severity of disruption caused by planned roadworks on Dutch roads. It provides the evidence base for designing realistic stated-choice scenarios in the subsequent chapters (both the attribute-based stated-choice experiment and the pivot module). First, using roadworks records from the Dutch National Traffic Data Portal (NDW), the chapter analyses when roadworks typically occur, how long they last, and how anticipated hindrance severity is classified, thereby grounding the temporal context (peak-period timing) and the typical duration of Dutch roadworks. In this thesis, duration is treated as a descriptive severity dimension that supports realistic scenario framing, rather than as an explicitly modelled choice attribute.

Second, a network impact case study in OMNITRANS translates representative roadwork conditions into additional travel-time impacts, thereby providing a plausible basis for the travel-time penalty magnitudes used to calibrate severity levels in the stated-choice components. Together, the NDW analysis and the OMNITRANS case study provide empirically grounded insights into the temporal context and typical duration of disruptions, as well as into additional travel time as the primary operational severity measure in the choice scenarios.

3.1. Data source and initial scope

The roadworks dataset is obtained from the NDW as part of the Situation Messages product group. This feed contains advance notice and planning information entered by road authorities for works and events that affect traffic flow, published in DATEX II (v2.3).

In this thesis, NDW is not used to directly estimate behavioural responses. Instead, it serves a design and grounding function, characterising how temporary roadworks typically vary in duration, anticipated disruption, severity, and time of day. These empirical patterns are used to motivate the disruption dimensions included in the stated-choice design, support the selection of representative high-impact conditions for scenario framing, and provide a Dutch-context benchmark that helps interpret the realism of the estimated choice responses in later chapters.

The starting point is three DATEX II XML exports of NDW roadworks messages (wegwerkzaamheden.xml.gz), downloaded on 29-09-2025, 22-10-2025, and 18-11-2025. Because NDW is a live feed that is updated throughout the lifecycle of a roadwork (planned, active, ended, overrun), repeated downloads result in multiple updates referring to the same underlying physical situation.

3.2. Data processing and construction of the analysis dataset

A key preprocessing step is to avoid repeated updates dominating descriptive results. In this thesis, a record refers to a single situationRecord as provided in the XML feed, while a situation refers to a unique NDW roadwork situation identifier (ID) after aggregation. ReroutingManagement is an NDW record type that often appears alongside MaintenanceWorks registrations for the same underlying roadworks situation. These records were therefore removed to avoid double-counting and to ensure that each roadworks situation is represented only once in the analytical dataset.

All records are aggregated by situation ID to yield a single observation per situation. For each ID, the earliest reported overall start time and the latest reported overall end time are retained to construct a conservative time envelope for the active period. For non-temporal attributes, one representative record is selected per situation based on completeness of information. This yields an analysis dataset at the situation level. Specifically, the representative record is selected as the update with the most non-missing fields among key descriptive attributes; ties are resolved by retaining the latest update timestamp.

The analysis focuses on September–November 2025 because the data were obtained through repeated snapshot downloads. All timestamps are converted from UTC to local Dutch time (Europe/Amsterdam), and the dataset is restricted to cases in which the local overall start time falls within the study window. To focus on temporary disruptions rather than long-running reconstruction projects, situations are retained only if their duration is strictly positive and at most 21 days.

Three derived variables are constructed to support the descriptive grounding of disruption severity:

- A road-group indicator that distinguishes A- and N-roads (including ring/motorway references) from other road contexts
- Peak-period overlap indicators for weekday morning (06:00–10:00) and weekday afternoon (15:00–19:00) windows, combined into a four-level peak exposure category: no overlap, morning only, afternoon only, and both peaks
- A hindrance indicator capturing anticipated delay severity (Section 3.3)

Importantly, the road-group indicator is used for stratified interpretation rather than as an upfront selection rule, so that the full dataset remains available for context.

3.3. Hindrance indicator and descriptive grounding

NDW provides the roadwork hindrance class (roadworkHindranceClass) as an expected delay category. This is mapped to a numeric scale from 0 to 4, where `hindranceClass0` corresponds to no delay and hindranceClass4 to the highest expected delay category (Table 3.1). The minute-range interpretations follow the NDW documentation and should be interpreted as categorical guidance rather than as realised delays.

roadworkHindranceClass	**Interpretation**
hindranceClass0	no delay
hindranceClass1	< 5 minutes delay
hindranceClass2	5–10 minutes delay
hindranceClass3	10–30 minutes delay
hindranceClass4	> 30 minutes delay

Table 3.1: NDW hindrance classes and interpretation.

Because the formal hindrance class is missing in a non-trivial share of cases, free-text public comments are used to derive an auxiliary qualitative hindrance classification using rule-based keyword patterns. The final hindrance indicator (hindrance_class_0_4) follows a priority rule: when the NDW hindrance class is available, it is used; otherwise, the text-derived classification is used where possible. To avoid losing information during aggregation, the pipeline also stores the maximum hindrance observed across updates within the same situation (hindrance_class_0_4_max), providing a conservative “maximum disruption” proxy.

3.3.1. Key patterns relevant for the survey design

Three descriptive dimensions are used to characterise typical roadworks exposure for commuters: duration, anticipated hindrance severity, and overlap with weekday peak windows. The main takeaways are as follows.

First, durations are strongly right-skewed, with most recorded situations being short (on the order of hours), while a smaller but relevant share persists for multiple days. This supports a stated-choice framing in which short- to medium-intervention periods can still affect multiple commuting cycles.

Second, hindrance severity in NDW is dominated by low- to moderate-expected-delay categories in the full dataset, whereas A/N-road situations are more concentrated in higher hindrance categories. This motivates focusing the stated-choice scenarios on the subset of "high-impact" conditions most likely to be salient to commuter adaptation decisions.

Third, peak exposure differs systematically by road type and duration. Peak overlap categories reflect both timing and persistence because longer active intervals mechanically increase the probability of overlapping both peak windows. Therefore, peak overlap descriptives are interpreted as indicative exposure patterns rather than as clear evidence on time-of-day effects.

Taken together, the NDW patterns provide empirical grounding for treating disruption severity as a joint construct of additional travel-time burden and temporal context (peak-period timing). In the commuting context used in this thesis, morning versus afternoon peak scenarios implicitly correspond to the outward versus return commute leg, without introducing commute direction as a separate modelled construct.

3.3.2. Discussion and data limitations

The NDW roadwork feed is a rich but challenging data source. Messages are created and updated by different road authorities, and several fields in the DATEX II schema are optional. As a result, key variables such as the formal hindrance class, start and end times, locations, and maintenance types are sometimes missing or only partially filled in. The analysis in this chapter builds on the available information and employs complementary strategies to extract additional value from the records. For example, free-text descriptions of the situation are exploited to infer qualitative hindrance levels when the formal hindrance class is absent. Similarly, durations are computed from the recorded start and end times. These derived measures should be interpreted as proxies: the timestamps are indicative rather than exact, since they reflect planned or administratively registered periods rather than systematically measured work intervals.

A further limitation is that the severity or delay of a roadwork is not observed ex post but is instead entered as an expected hindrance category when the message is created. The NDW hindrance classes should therefore be interpreted as judgment-based assessments by the road manager, not as precise measurements of realised delay. The combined hindrance indicator used in the analysis merges the formal hindrance class with the text-derived classification where needed, thereby improving coverage while retaining the original NDW information whenever available. To reduce sensitivity to within-situation updates, the analysis also retains the maximum hindrance value observed across updates for the same situation as a conservative proxy for peak severity.

3.3.3. Implication for the stated-choice design

Finally, the NDW analysis clarifies which types of situations are most relevant for commuter adaptation. It shows that commuter-relevant, high-impact works on main roads tend to be temporary interventions that can span multiple commute periods and are salient enough to plausibly trigger responses beyond simple rerouting.

This motivates the stated-choice design adopted in this thesis, which focuses on temporary capacity reductions on A- and N-roads that generate substantial additional car travel time and explicitly tests whether behavioural trade-offs differ across the temporal context of the commute, where schedule constraints and substitute performance vary. NDW grounds when and how long disruptions occur, and the case study below grounds how large the implied travel-time penalty can be under a representative high-impact configuration.

3.4. Case study A4 De Hoek – Burgerveen

To complement the aggregate insights from the NDW roadworks dataset, a more detailed examination of a specific motorway maintenance project was conducted. Whereas the descriptive statistics in the preceding sections characterise typical hindrance, duration, and road-type patterns across the Dutch network, they do not indicate the order of magnitude of additional car travel times that can result from a representative high-impact intervention. The purpose of this case study is therefore not to estimate behavioural responses, but to translate a realistic Dutch motorway works configuration into model-based travel-time penalties that can be used to specify severity levels in the stated-choice design.

For this purpose, a case study was selected involving maintenance work on the A4 between De Hoek and Burgerveen in the summer of 2025. These works were chosen because they represent a large-scale, well-documented intervention with clear implications for commuter traffic on a critical corridor in the Randstad, and because their operational features closely resemble the high-severity roadworks (hindrance classes 3–4) identified in the NDW-based analysis.

3.4.1. Description of the maintenance works

Maintenance activities on the A4 were conducted between 25 July and 21 August 2025. During this period, Rijkswaterstaat implemented a package of capacity-reducing measures, including reduced lane numbers, narrower lane widths, and a temporary 70 km/h speed limit throughout the work zone. In addition, several access points were temporarily closed, including the on- and off-ramps at Hoofddorp and Nieuw-Vennep. A particularly notable measure was the closure of the A5 connection from Raasdorp to De Hoek in the direction of Rotterdam and The Hague, which is usually a key link feeding traffic onto the A4. The service area Den Ruygen Hoek was also intermittently closed. Rijkswaterstaat advised travellers to expect severe delays, with estimates of up to 60 minutes during peak periods. The works also experienced a partial overrun, with narrowed lanes remaining in place on the A4 towards Amsterdam until 20 August (Ministerie van Infrastructuur en Waterstaat, 2025b). In terms of expected disruption severity, this event is therefore a strong example of the types of temporary works that play a central role in this thesis.

Figure 3.1: Map of the roadworks between De Hoek and Burgerveen. Source: (Noord-Holland, 2025).

3.4.2. Modelling approach using OMNITRANS

To quantify the project's network impacts in a controlled manner, the situation was reproduced in the calibrated regional transport model OMNITRANS. The analyses are based on the Noord-Holland Zuid (NHZ) traffic model for the municipality of Haarlemmermeer, which was made available for this research. The NHZ model is a macroscopic multi-modal network model implemented in OMNITRANS and routinely used for policy and project studies in the region. In this thesis, only the car assignment results for the morning peak are used, as the morning commute is typically the most schedule-constrained period and therefore a relevant benchmark for severe disruption exposure.

The purpose of this modelling exercise was twofold. First, it enables a systematic examination of how the imposed restrictions altered traffic flows and travel times across the corridor and its surrounding network under fixed demand. Second, the results provide an empirical foundation for selecting attribute levels in the stated-choice experiment, in particular, the ranges of additional travel time used in the scenarios. This strengthens the internal validity of the experiment by ensuring that respondents are confronted with changes in travel conditions grounded in a realistic Dutch case rather than chosen arbitrarily.

The case study was implemented as follows. Starting from the base-year NHZ model, the standard morning-peak origin–destination (OD) matrix for car traffic was retained unchanged to isolate the network exposure implied by the works. A static user-equilibrium assignment, as specified in the NHZ model documentation, was run for two scenarios: a reference network without roadworks and a work-scenario network with the A4 measures in place. In the reference scenario, the original network coding and link capacities from the municipal model were used.

For the work scenario, the network representation in OMNITRANS was modified to reflect the work conditions. The free-flow speeds and capacities of the A4 links affected by the maintenance were reduced in accordance with the temporary 70 km/h speed limit and reduced lane configuration. The A5 connection from Raasdorp to De Hoek in the southbound direction was removed from the network, effectively modelling it as fully closed. The access points at Hoofddorp and Nieuw-Vennep were similarly disabled to match the temporary closure of these ramps (Ministerie van Infrastructuur en Waterstaat, 2025b). Apart from these changes, all other network elements, OD matrices and assignment settings were kept identical to the reference run. These modifications ensured that the model reproduced the constrained traffic environment observed during the work in a controlled, reproducible manner.

With the adjusted network in place, OMNITRANS was used to recompute traffic flows and link travel times for the morning peak. Because the A4 is a central north–south corridor linking Amsterdam, Schiphol, Leiden and The Hague, the closure and capacity reductions forced substantial volumes of traffic to redistribute across parallel routes such as the A44 and several regional N-roads east and west of the A4. The model captures these diversion dynamics through travel-time-based assignment, enabling quantification of how displaced traffic loads adjacent corridors and how congestion propagates regionally.

3.4.3. Route-level travel time impacts and derivation of stated-choice attribute levels

To interpret the network-wide effects of the A4 works at the level of individual commuters, two illustrative origin–destination (OD) pairs were examined in more detail (one shorter regional relation and one corridor-crossing relation). For each OD pair, shortest-path routes were computed on the loaded OMNITRANS networks for both the reference situation without roadworks and the work scenario with the A5 connection closed and reduced capacities on the A4, using the morning-peak assignment outputs.

The first OD pair connects Schalkwijk and Papenveer. In the reference network, the fastest route follows A5, A4, and a short section of N207, with a modelled travel time of 24 minutes. When the A5 connection is removed, this direct route is no longer available and two main detour patterns emerge. One alternative remains on the A4 for longer and approaches the destination from the south. However, in the work scenario, the off-ramp normally used for this OD pair is also closed, forcing traffic to take an additional detour before reaching Papenveer. In the model, this option yields a travel time of 37 minutes, corresponding to an increase of approximately 54% relative to the reference. A second alternative diverts traffic via the N205, which offers spare capacity to absorb part of the flow that would normally use the A5 but introduces lower speeds and several signalised intersections. This route results in a travel time of 31.5 minutes, roughly 31% longer than in the no-works situation. Together, these detours illustrate that even when diversion options exist, affected car commuters can experience substantial increases in travel time of the order of 30–55%.

Figure 3.2 provides a visual summary of these diversion patterns for the Schalkwijk–Papenveer relation by contrasting the loaded network in the reference (left) and work (right) scenarios. The work-scenario panel clearly shows that flows previously using the A5 to access the A4 are redistributed to the longer A4-only detour and the N205 corridor, increasing traffic volumes and potential delays on these links.

(a) Reference situation

(b) Work-scenario situation

Figure 3.2: Indicative change in OD-pair travel times between the reference and work scenarios.

A second OD pair runs from Amsterdam-West to Leidschendam. Under normal conditions, the modelled morning-peak travel time is 35.5 minutes when the A5–A4 connection is available. Under the work scenario, the closure of the A5 link and the temporary capacity reductions on the A4 force traffic to take a longer route on the A4, using downstream access points. For this OD pair, the resulting travel time increases to 46.5 minutes, approximately 31% higher than the reference. This OD pair confirms that for commutes traversing the A4 work zone, the modelled additional delay typically ranges from 30% to 50%, depending on the availability and quality of alternative routes.

These results are summarised in Table 3.2. The table reports the modelled car travel times and percentage increases relative to the reference situation for both OD pairs and their main detour options.

Table 3.2: Modelled car travel times and percentage increases for two illustrative OD pairs.

OD pair	Route description	Travel time (min)	Increase
Schalkwijk–Papenveer	Reference (A5–A4–N207)	24	—
	A4-based detour without A5	37	+54%
	Detour via N205	31	+31%
Amsterdam-West–Leidschendam	Reference (A5–A4 corridor)	35	—
	Work-scenario route without A5	46	+31%

It is important to note that these results are obtained from a static macroscopic assignment. Static models approximate steady-state conditions in which demand is smoothly distributed over the analysis period and travellers instantaneously adapt to prevailing network conditions. In reality, day-to-day variability, incident-induced capacity drops, adverse weather and imperfect information can generate queue spillback and temporarily higher delays than those captured by a static equilibrium. The modelled percentage increases in Table 3.2 should therefore be interpreted as conservative averages rather than upper bounds on the experienced travel time losses. They nevertheless provide a realistic order of magnitude for the additional travel times that commuters can experience during high-severity motorway works in the Dutch context.

Based on these considerations, the additional travel-time levels used in the pivot module were specified as relative increases of 25%, 45% and 60% over the respondent's usual car commute. These levels are anchored in the OMNITRANS case study results: 25% represents a moderate but noticeable delay, 45% reflects substantial disruption consistent with the upper end of the modelled increases, and 60% captures very severe conditions consistent with the high-impact nature of the A4 maintenance project. The use of non-equidistant levels avoids imposing linearity in the behavioural response to severity. It allows the models reported later in the thesis to identify potential threshold effects when delays become extreme. The corresponding attribute specifications for the attribute-based stated-choice experiment are described in Chapter 4.

4
Experiment design

To address the main research question, an online survey was developed for employed commuters in the Netherlands who travel to work at least once per week. The survey is designed to elicit how commuters respond to temporary roadworks and associated road closures, both in hypothetical scenarios and in situations they have actually experienced. Rather than relying on a single type of question, the survey combines three complementary components that together capture different dimensions of commuter adaptation to planned roadworks. The first component is an attribute-based stated-choice (SC) experiment, which identifies how respondents trade off car use, public transport, and working from home under controlled hypothetical disruption scenarios. The second component is a pivot stated-choice (Pivot-SC) experiment that links disruption severity directly to each respondent's commute by expressing additional travel time as a percentage increase over the reported usual travel time. This makes it possible to examine whether adaptation behaviour changes once disruption becomes sufficiently large relative to the baseline commute and whether such responses differ across commuters with different constraints and levels of flexibility. The third component is a short revealed-preference (RP) module, in which respondents report how they actually responded when they experienced substantial roadworks or road closures in recent years. Taken together, these components allow the analysis to distinguish between general behavioural trade-offs, commute-specific sensitivity to disruption severity, and the extent to which stated responses correspond to reported real-world behaviour.

The first component is an attribute-based stated-choice (SC) experiment. In this part of the survey, respondents are presented with stylised roadwork scenarios and asked to choose between different commuting options for the next working day. The second component is a pivot stated-choice (Pivot-SC) experiment that links disruption severity directly to each respondent's own commute. In this section, additional car travel time is expressed as a percentage increase over the usual one-way travel time reported earlier in the questionnaire. The third component is a short revealed-preference (RP) module. Respondents are asked whether they have experienced substantial roadworks or road closures affecting their commute in the past few years and, if so, how they actually responded.

All respondents in the sample are employed and completed the SC experiment. The Pivot-SC and RP components were administered only to respondents who reported commuting to work by car and having a car available for that commute.

In the remainder of this chapter, these three components are discussed in turn. First, the commuting alternatives that appear across the SC and Pivot-SC experiments are specified. Subsequently, for both SC components, the context, alternatives and attributes are described, followed by the specification of attribute levels and the experimental design. Finally, the RP module is outlined, including the question content and its role in assessing how stated responses compare to behaviour in real closures.

4.1. Alternatives

In principle, many responses to temporary roadworks can be identified, such as changing departure time, changing route while staying in the car, using another road-based mode, switching to public transport, WFH, or cancelling the trip. Including many alternatives would increase data richness but also make the choice tasks more complex (Weng et al., 2017). More importantly, this thesis does not aim to model the full set of possible adaptations equally. Instead, it focuses on the three responses most central to the research question and most relevant to understanding how disruption severity may reduce routine car commuting among working commuters: continuing by car, switching to PT, and working from home. Together, these alternatives capture the main substitution pathways through which commuters may either persist in car use, shift to another mode, or avoid the trip altogether. Intramodal responses are treated more selectively within this design: rerouting is captured only indirectly through the resulting travel time and cost of the car alternative, whereas retiming is not represented as a separate choice option in the stated-choice tasks.

In this study, three alternatives are included in each stated choice situation:

- **Car**. The respondent travels to work by car on a typical day, but the trip is affected by roadworks. This alternative represents continued car commuting under disrupted conditions. Possible rerouting is captured only indirectly through the resulting travel time and cost of the car trip, since the design does not distinguish between specific routes. Retiming, however, is not modelled as a separate choice within the stated-choice tasks.
- **Public transport**. The respondent travels to work by public transport instead of by car. The public transport alternative includes all access and egress components of a typical PT commute and is presented as a single, generic PT option.
- **Working from home**. The respondent does not travel to the workplace on that day and works from home instead.

These three alternatives therefore operationalise the main behavioural pathways through which planned roadworks may alter commuter demand in this thesis: persistence in car use, intermodal substitution to PT, and non-travel substitution through WFH. The same three alternatives are offered in both stated-choice blocks; the difference between the blocks lies in how the commute and the disruption are described.

4.2. Attribute-based stated-choice experiment

The empirical design therefore focuses on substitution between continued car use, PT, and WFH, while recognising that some within-car adaptations, especially rerouting, may be embedded in the realised burden of the car option and that retiming remains outside the explicit behavioural scope of the choice experiment.

4.2.1. Context

In the stated-choice experiment, respondents evaluate stylised commuting situations in which temporary roadworks affect travel between home and a fixed workplace. Each choice task is introduced by a short scenario describing a hypothetical commute (origin, destination, and typical car travel time), followed by an explanation of how temporary roadworks affect the car route. Respondents are explicitly asked to imagine that this is their commute for the next working day and, for each scenario, to choose between travelling by car, switching to PT, or working from home.

The SC experiment targets employed respondents who commute to a workplace at least once per week. This ensures that the described situations are relevant for the sample and that the scenarios reflect a meaningful commuting decision for the next working day. To ensure a consistent interpretation of the tasks, each stated-choice scenario should be read as a decision for the next working day. The travel time and travel cost values shown in the choice task refer to a single one-way trip of the respective alternative. When both directions are affected, respondents should interpret the same per-trip disruption conditions as applying to both the outward and return commute on that day.

Trip purpose

Travel behaviour during disruptions is known to depend on trip purpose. In this study, the focus is on situations in which disruptions have the most significant societal impact, namely commuting to work. Commuters form a substantial share of peak-period traffic and are often constrained by work start times. Therefore, the trip purpose in all attribute-based SC scenarios is fixed to travel from home to the workplace.

Type of disruption and information provision

The attribute-based SC experiment concentrates on temporary reductions in road capacity on the main commuting route, such as lane closures, reduced speed limits, or temporary full closures of a link. It is assumed that these works are announced in advance by the road authority or are visible in navigation and travel-planning applications.

In each scenario, the roadworks are described in general terms, and their consequences are reflected in the resulting car travel time and cost shown in the choice table. The introductory scenario text also specifies which part of the commute is affected (morning peak, evening peak, or both) and the day-specific WFH context (WFH feasible, hybrid day, or on-site expected) for that next working day.

Working from home context

An essential feature of the attribute-based SC experiment is the option to replace commuting with WFH. However, not every day is equally suitable for working from home. The scenario description, therefore, also specifies whether, on that particular day, the commuter is expected to be physically present at the workplace, can work from home if desired, or faces an intermediate situation. This day-specific WFH context varies across scenarios and interacts with the WFH alternative in the choice tasks, enabling analysis of how organisational flexibility and expectations influence the propensity to work from home when roadworks cause additional delays.

Time of day and direction

Responses to disruptions may differ between the outward and the return trip. If a disruption occurs on the way home, commuters may adjust their return timing, whereas a disruption in the morning may interact more strongly with WFH feasibility. To capture such asymmetries while keeping the choice setting comparable across tasks, the attribute-based SC experiment varies the time of day and direction of the disruption between scenarios: only the outward trip in the morning peak is affected, only the return trip in the evening peak is affected, or both trips are affected.

Respondents are instructed to assume that information about the roadworks is available before they decide whether and how to travel, so that their choices in the SC tasks represent ex ante decisions for that day rather than reactions during the travel.

4.2.2. Attributes

Each alternative is described by a small set of attributes that vary between choice tasks. Many factors could, in theory, be included, such as travel time, travel cost, reliability, duration of disruption, information, and WFH. Including too many attributes, however, can overload respondents and lead them to ignore some attributes or make their own assumptions about unspecified aspects (Caussade et al., 2004).

To keep the experiment focused and tractable, the explicit attribute set in the attribute-based stated-choice block is restricted to two generic attributes that summarise the main consequences of the disruption for the commute:

- **travel time (TT)** expressed in minutes per single trip;
- **travel cost (TC)** expressed in euros per single trip.

For the car alternative, both TT and TC vary between choice tasks. For PT, only TT varies; TC is fixed at EUR 12 per trip to reflect typical commuting fares and is therefore not treated as an estimable attribute in the utility specification. For WFH, both travel time and commuting costs are set to zero because there is no physical commute on that day. Other factors identified in the conceptual framework, such as the timing of the disruption and day-specific WFH requirements, are treated as context variables. They are not shown as rows in the choice table; instead, they appear in the scenario description above the table, where they are entered as scenario-specific constants.

Travel time is entered into the utility functions as an alternative-specific continuous variable, with separate coefficients for car and PT. Travel cost is entered as an alternative-specific continuous variable for the car alternative only. In the base specification, TT and TC are assumed to affect utility linearly over the range of levels used in the design.

4.2.3. Travel Time

A further design choice concerns the baseline commuting situation on which the attribute levels are defined. In the attribute-based block, respondents are asked to imagine a commute in which, on a normal day without roadworks, the car trip from home to work takes approximately 35 minutes. This value is close to the average commuting time for employees in the Netherlands reported in recent national statistics, and therefore provides a realistic reference point for the hypothetical scenarios (Centraal Bureau voor de Statistiek, 2024i). The attribute levels shown in the experiment should then be interpreted as the resulting travel times and costs on a day with roadworks, conditional on this baseline.

For each attribute, three design aspects must be specified: the number of levels, the range of those levels, and the spacing between levels (METRICS, 2025). Attribute levels for travel time (TT) and travel cost (TC) are chosen such that each level appears approximately equally often across the choice tasks. This improves the precision of the parameter estimates over the full range of attribute values.

The range of travel time levels must be broad enough to identify meaningful trade-offs, but not so broad that alternatives become implausible or obviously dominated. Descriptive analyses of roadworks data and prior studies indicate that temporary capacity reductions often lead to additional delays that constitute a modest to substantial share of typical commuting time. In contrast, very extreme delays are less frequent. The car travel time levels in the design, therefore, span a range from a relatively small increase relative to a regular commute to a clearly disruptive increase. The normal car travel time in the scenario is fixed at 35 minutes, and the attribute levels correspond to additional delays of 10, 25 and 35 minutes. On days with roadworks, the car alternative is therefore presented with travel times of 45, 60 and 70 minutes.

The range of car travel time levels in the attribute-based experiment is chosen to be broadly consistent with the order of magnitude observed in the A4 De Hoek–Burgerveen case study, while remaining simple and interpretable for respondents. The OMNITRANS results in Section 3.4 indicate that representative OD-pair travel times under the work scenario typically increase by roughly 30–55% compared with the reference situation. The lowest design level of 45 minutes corresponds to an increase of about 30% relative to the 35-minute baseline, representing a moderate disruption. The intermediate level of 60 minutes implies an increase of about 70% and reflects severe conditions in which both diversion and congestion effects play a role. The 70-minute level approximately doubles the normal travel time. It represents very severe conditions that are within the same order of magnitude as high-impact motorway works, where authorities warn of delays of up to an hour during peak periods. Together, the three levels (45, 60 and 70 minutes) thus cover a spectrum from moderate to very severe delay and allow the discrete choice models to detect possible threshold effects when delays become very large.

For the PT alternative, travel time levels are calibrated relative to the baseline car travel time. Empirical comparisons suggest that PT travel times for commuting are, on average, between 1.25 and 1.43 times car travel times, depending on access mode and network structure (CROW, 1998). Because access and egress are not specified in the survey, a factor near the upper end of this range is used for the design calibration. For a 35-minute reference car commute, this implies a PT travel time of approximately 50 minutes ($35 \times 1.43 \approx 50$). The design therefore uses PT travel times of 50, 55 and 60 minutes. In the questionnaire, respondents only see the resulting absolute travel times in minutes.

4.2.4. Travel Cost

Travel cost levels are chosen to reflect realistic ranges for medium-distance commuter trips in the Dutch context. For the car alternative, travel costs are based on the variable cost per kilometre. The variable cost of car use is approximated by EUR 0.23 per kilometre (Warnaar et al., 2024). For the stylised commute in the attribute-based block, the car trip is assumed to cover approximately 45 km, corresponding to about 35 minutes of driving at an average speed on main roads. The variable cost per single trip is then.

$$C_{\text{var,car}} = 0.23 \times 45 \approx \text{EUR } 10.35.$$

On days with roadworks, the car trip becomes longer and more costly due to additional fuel consumption and time spent in congestion. To motivate plausible cost levels, the cost of the car on a disrupted day is approximated as a linear function of the additional travel time:

$$C_{\text{car}}(t_{\text{extra}}) = C_{\text{var,car}} + 0.10 \times t_{\text{extra}},$$

where t_{extra} denotes the extra minutes of travel time compared with the usual 35-minute commute. For the three car travel time levels in the design, corresponding to additional delays of 10, 25 and 35 minutes, the approximate costs per single trip are EUR 11.35, EUR 12.85 and EUR 13.85, respectively. These values are rounded to the nearest euro and used as candidate levels in the design, so that the travel cost attribute for the car alternative takes the levels EUR 11, EUR 13 and EUR 14 per trip. Importantly, TT and TC were varied independently in the experimental design; the above calculation is used only to select realistic TC levels.

For PT, travel cost is fixed at EUR 12 per trip to reflect typical Dutch commuting fares (Warnaar et al., 2024). Because roadworks affect only the car route and not the PT supply, this PT cost level is kept constant across all scenarios in the attribute-based block.

WFH is always shown with a travel time of 0 minutes and a travel cost of 0 euros, as there is no physical commute on that day.

Table 4.1 summarises the attribute levels used in the attribute-based SC block.

Table 4.1: Attribute levels for the attribute-based stated choice block (per single trip).

Alternative	Attribute	Levels
Car	Travel time (TT)	45, 60, 70 minutes
Car	Travel cost (TC)	EUR 11, EUR 13, EUR 14
Public transport	Travel time (TT)	50, 55, 60 minutes
Public transport	Travel cost (TC)	EUR 12
WFH	Travel time (TT)	0 minutes
WFH	Travel cost (TC)	EUR 0

4.2.5. Scenario variables

Two scenario variables are varied across the choice tasks through the introductory text above the attribute table, rather than as additional rows in the table itself. These variables capture contextual factors expected to interact with the attractiveness of the choice options.

The first scenario variable describes the WFH context for that particular day. Three qualitative levels are distinguished, reflecting different expectations from the employer regarding physical presence at the workplace:

1. WFH feasible: the respondent has no on-site appointments and can carry out all tasks from home.
2. Hybrid day: the respondent has several meetings; in-person attendance is preferred, but online participation is possible.
3. On-site expected: the respondent is expected to be physically present at the workplace.

These levels are incorporated directly into the scenario text. In the utility specification, they will be represented by dummy variables that interact with the WFH alternative-specific constant, allowing the analysis to capture how employer expectations about presence on a given day affect the propensity to WFH in response to roadworks.

The second scenario variable captures when (and in which direction) the disruption affects the commute. Responses to roadworks may differ between the outward and the return trip.

1. Morning peak (outward trip): the roadworks affect the trip from home to work.
2. Evening peak (return trip): the roadworks affect the trip from work to home.

3. Both directions: the roadworks affect both the morning and evening trips.

In all cases, the travel time and travel cost levels shown in the choice table refer to a single trip of the respective alternative. When both directions are affected, the same disruption level applies to both trips (morning and evening), again interpreted per trip.

Across all scenarios, the stated-choice question represents a day-level decision for the next working day. The travel time and travel cost values shown in the table refer to a single one-way trip. When both directions are affected, respondents should interpret the same per-trip conditions as applying to both legs of the commute on that day; choosing WFH implies that neither leg of the commute is made.

By varying the time of day and direction across scenarios, the design allows testing whether commuters respond differently to disruptions in the morning versus the evening, and whether impacts compound when both trips are affected. In particular, it enables analysis of how the WFH option is used as an alternative to travelling when the outward trip is disrupted, compared to situations in which only the return trip is affected.

4.2.6. Conceptual framework for the attribute-based SC block

In the attribute-based stated-choice block, only a subset of the determinants from the general conceptual framework is explicitly operationalised. Figure 4.1 highlights these elements in black. Trip characteristics are restricted to commuting between home and the workplace, while the time of day and direction affected by the disruption (morning, evening, or both) vary across scenarios. Other trip aspects, such as distance and route familiarity, are kept constant and therefore shown in light grey. Work and organisational context enter the experiment through the day-specific WFH context described in the scenario text.

Within the disruption characteristics, the key variables that vary across choice tasks are the additional travel time due to roadworks and the timing/direction of the disruption. Information provision is assumed to be adequate and known in advance, so that choices represent ex ante decisions. Accessibility and performance of alternatives during the disruption are captured by the travel time of the car and public transport alternatives (with public transport cost held constant in this block) and, implicitly, by their perceived reliability during the works.

At the bottom of the framework, the three broad categories of behavioural response are retained. In the design, mode shift and replace/cancel trip correspond directly to the public transport and WFH alternatives shown in the choice table. Within the modify-trip category, rerouting is not offered as a separate alternative but may be reflected indirectly in the higher travel times and costs of the car option. Retiming is conceptually relevant but is not represented as a separate behavioural response in the attribute-based stated-choice design. Accordingly, only the explicitly operationalised elements are shown in black.

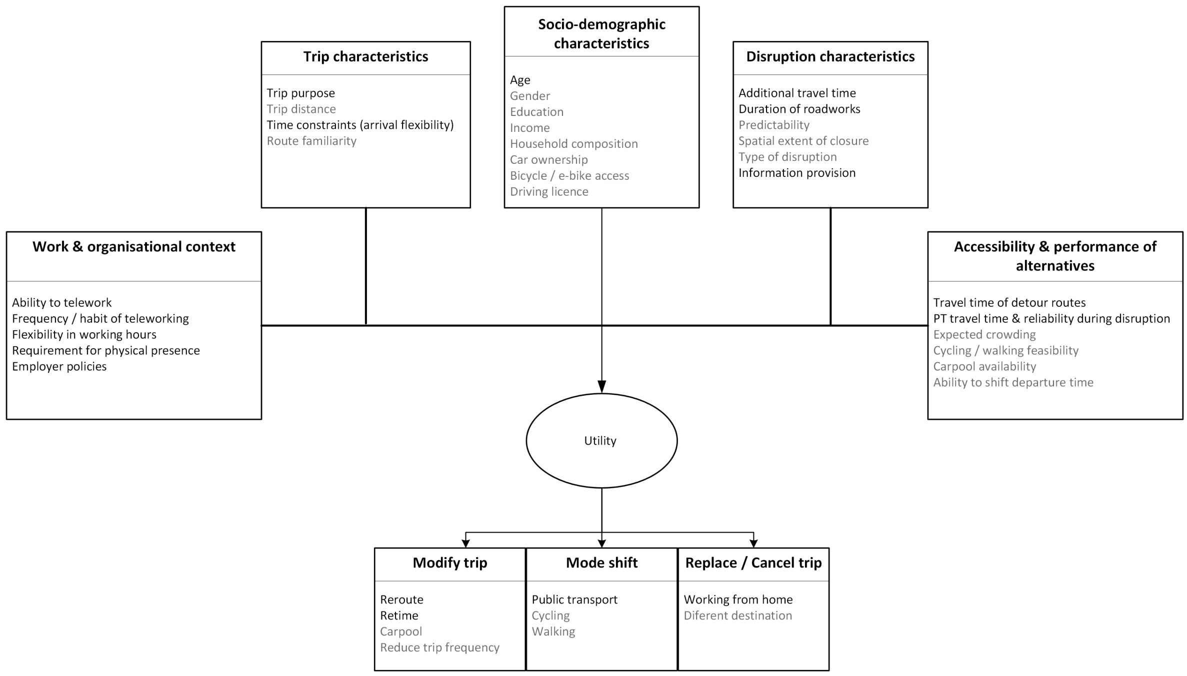


Figure 4.1: Conceptual framework for the attribute-based SC block.

4.3. Pivot stated-choice question

In the pivot stated-choice question (pivot-SC), respondents evaluate a disruption on their own commute rather than on a stylised reference trip. Unlike the attribute-based block, this component does not use an attribute table. Instead, it focuses on how car commuters respond when the travel time of their usual car trip to work increases due to temporary roadworks. This block is only shown to respondents who report that they usually commute to work by car and have a car available for that commute.

Earlier in the questionnaire, respondents reported their usual one-way car travel time to work. The reported time, denoted by X, serves as the individual-specific baseline for the pivot question. The scenario text recalls this baseline and then describes increased travel time due to temporary roadworks. A generic wording is:

> ”You indicated that your usual car trip to work takes about X minutes. Because of temporary roadworks on your route, this trip would now take about Y minutes.”

Here, Y denotes the longer travel time due to the works, and the difference $\Delta = Y - X$ captures the severity of the disruption. The design specifies three relative increase levels, corresponding to approximately 25%, 45% and 60% increases in travel time relative to the respondent's usual commute. These percentages are informed by the OMNITRANS case study of the A4 De Hoek–Burgerveen works (Section 3.4), which provides an order-of-magnitude benchmark for plausible high-impact motorway works, rather than a one-to-one calibration of the stated-choice levels. In the case study, representative OD pairs experienced increases in modelled travel time of roughly 25–55%. To reflect this range, and to allow for somewhat more severe conditions, the pivot design therefore uses three severity levels $\delta \in \{0.25, 0.45, 0.60\}$ and computes

$$Y = X \times (1 + \delta).$$

In the questionnaire, only the rounded value of Y in minutes is shown; the percentages themselves are not presented to respondents. Each respondent answers all three severity levels in random order.

This question has the same three alternatives as the attribute-based block: continue travelling by car with the longer travel time, switch to public transport, or work from home. No further attributes or numeric levels are presented in this block. Instead, respondents are expected to evaluate the public transport and WFH options based on their own situation.

To obtain a rich behavioural profile of the respondents who answer the pivot questions, the questionnaire includes a set of background items on work arrangements and commuting conditions. These questions are asked in earlier sections of the survey and are not repeated next to the pivot itself. In the analysis, they are linked to the pivot responses, allowing examination of how sensitivity to delay and the choice between car, public transport, and WFH depend on WFH options, job flexibility, and the accessibility of alternative modes. In this way, the pivot-SC block not only measures average reactions to longer car travel times but also how these reactions vary across worker types and commutes.

4.3.1. Working from home context

A first group of questions characterises whether and how respondents can realistically work from home. Empirical studies show that only workers with both organisational permission and suitable tasks increase WFH in response to disruptions; for others, the option is effectively unavailable (Chalabi & Dia, 2024; Thompson et al., 2021). The questionnaire, therefore, first distinguishes between jobs that are strictly location-bound, jobs where WFH is possible but restricted, and jobs where WFH is generally possible.

For respondents who indicate that WFH is possible to some extent, follow-up questions capture:

- The number of days per week they are allowed to work from home
- The number of days per week they actually work from home in a normal situation
- Whether WFH days can be shifted to other days when that would be more convenient
- Whether their work contains specific tasks that can only be carried out on site
- Their evaluation of the home working environment

Together, these items summarise both WFH feasibility and WFH habits. In the modelling stage, the WFH alternative will be treated as effectively unavailable for respondents with strictly location-bound jobs, and as more attractive for those who are allowed to WFH several days per week, who already use this option frequently and who evaluate their home workplace positively. This enables analysis of pivot responses to reveal, for example, whether commuters with flexible WFH arrangements are more likely to switch to working from home when their car commute becomes substantially longer.

4.3.2. Commute and accessibility context

A second group of background questions describes the respondent's usual commute and the relative accessibility of car and public transport. The literature on behaviour during temporary closures shows that baseline travel times, mode use and access conditions strongly influence which adaptations are feasible and likely (Ye et al., 2012). The questionnaire, therefore records:

- the usual one-way travel time on a normal workday (in minutes);
- the main mode used for the commute on a normal day (car, public transport, walking or cycling);
- whether the respondent has a car available that could be used for the commute.

Additional items ask, among other things, whether the respondent uses a leased car, whether the employer reimburses commuting costs by car and/or public transport, how the respondent usually accesses public transport, and how long a public transport trip to the workplace would take under normal conditions.

These variables provide information on both the objective and perceived accessibility of the alternatives. Existing occasional public transport users are, for example, more likely to switch to public transport during a closure than commuters who never use it (Ye et al., 2012). Similarly, commuters with a leased car and full cost compensation may perceive car use as relatively cheap, which is expected to reduce the sensitivity to travel cost differences and to make mode shift less likely (Bueno et al., 2017). In the analysis of the pivot experiment, these background characteristics will therefore be used to explain systematic differences in how individuals react to the same percentage increase in car travel time.

4.3.3. Conceptual framework

In the pivot stated-choice question, the general conceptual framework is applied to respondents' own commute rather than to a stylised trip. Figure 4.2 highlights the elements that are active in this block.

Trip characteristics and work- and organisational-context variables enter directly, because the disruption is defined relative to each respondent's reported baseline car commute. These factors are not manipulated experimentally; they are observed and subsequently used to explain heterogeneity in responses.

Disruption severity is represented by the additional travel time on the usual car route. At the same time, information provision is assumed to be adequate and known in advance. Accessibility and performance of alternatives are captured by respondents' own public transport options and constraints, as well as reported access conditions and perceived service quality. At the bottom of the framework, the three behavioural pathways are again distinguished: modify trip, mode shift and replace/cancel trip. Within the modify-trip category, rerouting may be reflected indirectly in the car alternative through increased travel time due to the disrupted commute. Retiming is conceptually relevant but is not represented as a separate behavioural response in the pivot stated-choice design. Mode shift and replace/cancel trip correspond directly to the explicit public transport and WFH alternatives. Together, the highlighted elements show how the pivot-SC block relates disruption severity on the actual commute to the probabilities of continuing by car, changing mode or working from home.

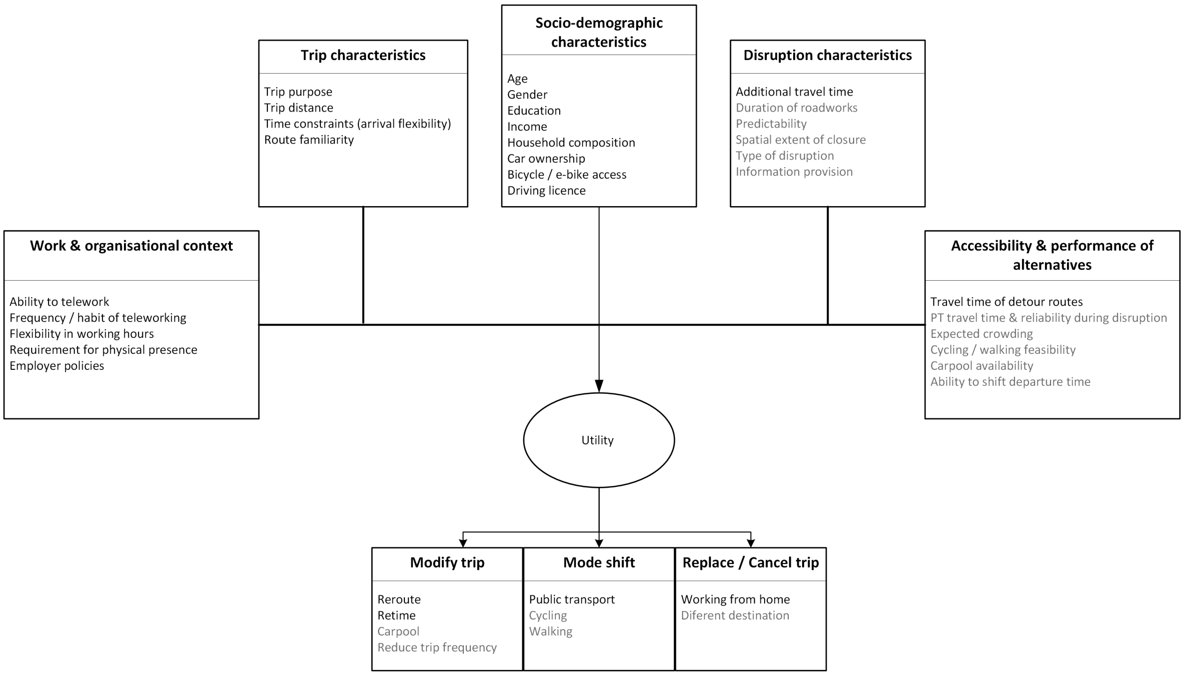


Figure 4.2: Conceptual framework for the pivot-SC block.

4.4. Revealed-preference question

In addition to the stated-choice components, the questionnaire includes a short revealed-preference (RP) module. Whereas the stated-choice blocks elicit responses to hypothetical disruption scenarios, the RP questions record how respondents report having responded when they experienced substantial roadworks or road closures on or near their own commuting route in the past few years. This module is only shown to respondents who report that they usually commute to work by car and have a car available for that commute. The RP module does not elicit disruption severity in minutes or days. It is therefore used as an external plausibility check on realised behaviour rather than as a severity-conditioned estimate.

The RP module consists of three questions. First, a screening question asks whether respondents have experienced substantial hindrance in the past few years due to road closures or major roadworks on or near their usual route to work. Only respondents who answer yes proceed to the follow-up questions.

Second, these respondents are asked how they responded during that disruption. The answer categories mirror the three main behavioural responses that are central to this thesis:

- continuing to commute by car while accepting extra travel time
- switching to public transport
- working from home instead of travelling.

Third, an open follow-up question invites respondents to briefly describe the type of roadworks involved and the approximate location (A4 near Hoofddorp, one-lane closure for several weeks”). These free-text descriptions provide contextual information on the type and approximate scale of the disruptions reported in the RP module.

The RP information serves two analytical purposes. First, it enables a descriptive assessment of how car commuters report responding when they experience substantial roadworks on their usual route, using the same three options as in the stated-choice blocks (car, public transport, WFH). Within this RP categorisation, continued car commuting does not distinguish between unchanged car travel and within-mode adaptations such as rerouting or retiming. Second, it enables a basic consistency check between stated and revealed responses. In this way, the RP module complements the two stated-choice components: the attribute-based SC experiment identifies behavioural trade-offs under controlled conditions, the Pivot-SC module tests how these responses vary when disruption is anchored to the respondent’s own commute, and the RP evidence provides a cautious empirical check on whether similar adaptation patterns are reflected in reported real-world behaviour. For example, respondents who report that they continued by car with additional delay in the RP module but systematically choose public transport or WFH in the stated-choice tasks under comparable disruption levels can be identified in sensitivity analyses. This helps to interpret the model results and to assess the robustness of the conclusions drawn from the stated-choice data.

4.5. Ngene implementation and blocking

Ngene was used to generate a statistically efficient and well-balanced design for the specified MNL utility structure. In particular, the design aims to avoid dominated alternatives and to achieve an approximately balanced occurrence of attribute levels across choice tasks. Importantly, although the car travel-cost levels were motivated using variable-cost calculations, travel time and travel cost were treated as separate attributes and varied independently in the experimental design.

Ngene specification and efficiency

The attribute-based design was generated using Ngene with a multinomial logit (MNL) specification consistent with the utility structure described earlier in this section. For the car alternative, travel time and travel cost were entered as alternative-specific continuous variables. For public transport, only travel time was entered as a continuous variable, as the fare was fixed in the choice tasks and is therefore not an estimable attribute. WFH was represented by an alternative-specific constant only. Although the car travel-cost levels were motivated by variable-cost calculations, travel time and travel cost were treated as separate attributes in the experimental design and were not deterministically linked.

Design quality checks (dominance and attribute correlation)

Two ex post checks were performed on the final blocked design (Appendix D). First, to confirm that car travel time and car travel cost were not collinear, the Pearson correlation between them was computed across the 12 tasks. The correlation is low ($r = -0.11$), indicating that cost is not mechanically implied by time in the design, supporting the separability of the corresponding parameters in the MNL specification.

Second, the final design was evaluated for dominance patterns between the car and PT regarding the displayed travel attributes. The design was constructed to minimise dominance and to ensure that tasks featuring dominance were balanced rather than concentrated in one direction. In particular, cases where the car is faster and cheaper and cases where the PT is faster and cheaper, both occur, and this balance is maintained across the two blocks so that neither block systematically favours one alternative. This reduces the risk that choices are driven by trivial dominance rather than by meaningful trade-offs. Ngene’s swapping algorithm was used because it combines high efficiency with a near-balanced distribution of attribute levels across the design (METRICS, 2025). The algorithm produced a design with 12 choice tasks. The resulting D-error and A-error are 0.0668 and 0.293, respectively, indicating a satisfactory level of statistical efficiency for the intended sample size. The full Ngene syntax and output are documented in Appendix B and Appendix C.

Context integration and blocking

As discussed in the previous subsection, two scenario variables are varied across choice tasks: WFH context and the time-of-day exposure of the disruption (morning peak, evening peak, or both). These context variables were not included as additional attributes in the Ngene specification. Instead, a separate factorial design of WFH context and disruption timing was constructed and then combined ex post with the 12-row attribute-based design. This balanced extension ensures even coverage of the context space while keeping attribute design optimisation manageable.

To limit respondent burden, the 12 resulting context–choice combinations were divided into two blocks of six choice tasks each. Every respondent is randomly assigned to one of these blocks in the online survey. This yields a maximum of six choice tasks per respondent in the attribute-based block. Respondents who report that they usually commute to work by car and have a car available additionally complete the three pivot stated-choice questions and the revealed-preference module, keeping the total completion time within acceptable bounds.

4.6. Questionnaire design

The online questionnaire was implemented in Qualtrics and consists of a sequence of blocks with simple routing logic, as summarised in Figure 4.3. Respondents first see an opening text with study information and informed consent. They then answer socio-demographic questions, followed by blocks on WFH possibilities, flexibility of work times and location, and commuting behaviour. Next, respondents are introduced to the stated-choice experiment and complete one block of six attribute-based SC tasks, followed by the three pivot-SC questions. Finally, car commuters receive the short revealed-preference module. The full explanation and overview of the survey are provided in Appendix E.

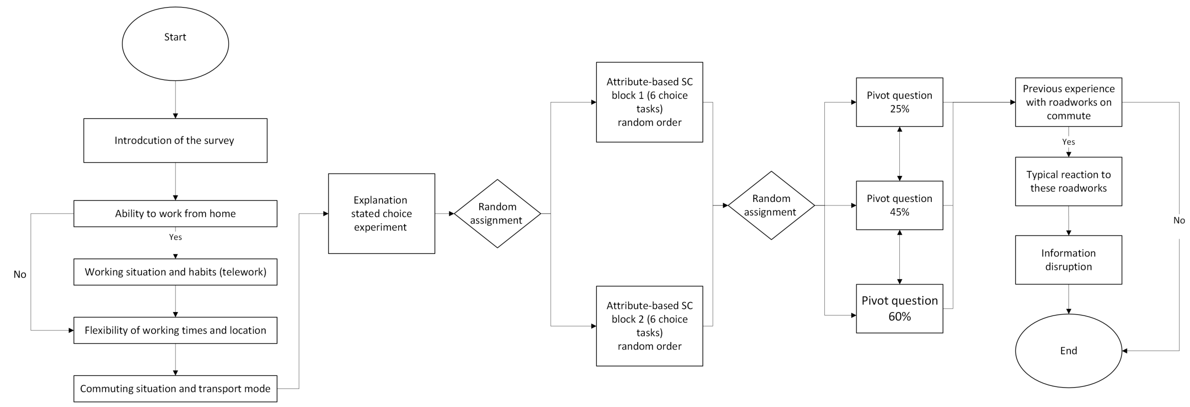


Figure 4.3: Overview of the survey structure.

4.6.1. Recruitment procedure

This study used an online survey administered through Qualtrics. Recruitment followed a broad, convenience-based strategy to reach working commuters from diverse backgrounds and work contexts. The survey link was distributed through three main channels.

First, the survey was disseminated internally within Sweco. The accompanying message explicitly encouraged employees, where possible, to share the survey within their own groups and networks to reach a wider range of respondents. Second, the survey was shared publicly via LinkedIn. The post was re-shared by multiple individuals, helping the survey circulate across personal and professional networks. Third, the survey was distributed via personal channels within and around the author's networks.

The survey was open from 19 December 2025 to 21 January 2026. Over this fieldwork period, a total of 234 responses were collected. The modelling analyses in later chapters use a cleaned analytical sample after applying the quality and consistency filters described in the data preparation section.

A formal response rate cannot be reported for this study. The Qualtrics link was open and anonymous, so the total number of people reached or invited is unknown. In addition, because no source tracking was implemented, it is not possible to determine which channel respondents used to enter the survey.

Taken together, the recruitment strategy supports the collection of behavioural data across a heterogeneous set of respondents. Still, it also implies that the results should be interpreted with caution when making population-level generalisations. The primary strength of the dataset lies in identifying and testing behavioural mechanisms and heterogeneity within the observed sample. At the same time, statements about transferability to the wider Dutch commuter population should remain bounded by the documented sample composition.

Sample size considerations

The required sample size in stated-choice experiments depends on the number of tasks per respondent, the number of alternatives, and the complexity of the attribute level structure. As a commonly used rule-of-thumb, the minimum sample size can be approximated as $N \geq \frac{500c}{ta}$, where c is the largest number of levels for any attribute, t is the number of choice tasks per respondent, and a is the number of alternatives per task (de Bekker-Grob et al., 2015). In this study, $c = 3$, $t = 6$, and $a = 3$, implying a minimum of approximately $N \geq 84$ respondents for reliable main-effect estimation. The final analysed sample ($N = 180$) exceeds this heuristic and yields up to $180 \times 6 = 1080$ choice observations, providing sufficient information to estimate the intended MNL specification and the key interaction effects.

5 Descriptive statistics

5.1. Filtering criteria and rationale

The raw Qualtrics export contains $N = 234$ rows. Subsequent filtering focused on completion quality (progress), minimum completion time to remove speeders, plausibility of reported one-way commute durations, completeness of the SC task sequence, and availability of the reported main commuting mode. Table 5.1 summarises the filtering steps and the resulting sample sizes.

Table 5.1: Data cleaning steps and resulting sample sizes.

Step	N
Raw export (including embedded label row)	234
Remove embedded label/metadata row	233
Completion quality (Progress $> 90\%$)	200
Remove speeders (Duration > 150 seconds)	188
Commute-time plausibility (Duur_reis < 140 minutes)	186
SC completeness: assigned SC block fully completed (six SC tasks)	182
Reported main commuting mode available	180

Five primary inclusion filters were applied to remove low-quality responses and implausible commuting records. First, only respondents with sufficient survey completion were retained:

$$\texttt{Progress} > 90\% \tag{5.1}$$

This criterion ensures that respondents were exposed to the core parts of the questionnaire and that key background variables and choice tasks were answered. Very low completion responses often correspond to break-offs that do not provide a coherent behavioural profile.

Second, a minimum completion time threshold was applied to remove speeders:

$$\texttt{Duration (in seconds)} > 150 \text{ seconds} \tag{5.2}$$

Online surveys are vulnerable to respondents who rush through the instrument without reading the tasks properly. Setting a conservative minimum duration reduces noise in subsequent descriptive patterns and prevents biased choice shares driven by random clicking.

Third, a plausibility filter was applied to the reported one-way commute duration:

$$\texttt{Commute-time plausibility} < 140 \text{ minutes} \tag{5.3}$$

Extremely long reported commuting times can reflect misinterpretation of the question, outliers that are not representative of regular commuter travel, or erroneous entries. Because commute duration is a key contextual variable in later descriptive analyses and interpretation of behavioural adaptation, limiting extreme values improves interpretability and comparability across respondents.

Fourth, a completion filter was applied to the SC component. The SC component consists of six choice tasks per respondent, within a single assigned block. Respondents were retained if their assigned SC block was fully completed. This ensures a consistent panel structure and avoids biased descriptive choice shares driven by partial task completion.

Finally, two respondents were excluded because they did not report their main commuting mode, which is required for the travel-context descriptives and for constructing mode-specific subsamples used later in the analysis.

These filters jointly define the cleaned analytical sample used for the descriptive statistics in this chapter and for the construction of the modelling datasets.

5.2. Reference populations

Table 5.2 benchmarks the cleaned survey sample ($N = 180$) against two reference populations: the Dutch adult population and the Dutch road-active population. The Dutch population benchmark provides a general representativeness check for socio-demographic characteristics. However, the SC experiment is designed around behavioural responses in a commuting and travel-demand context, and the pivot and RP modules were administered only to respondents who usually commute by car. For this reason, the road-active benchmark is a behaviourally more relevant comparator for those parts of the data, as it represents individuals who actually participate in road-based travel on an average day. The construction and justification of the numbers per category can be found in Chapter F.

The comparison indicates that the sample is structurally skewed toward certain socio-demographic groups. In terms of gender, the sample contains a higher share of men (61.1%) and a lower share of women (31.7%) than both the Dutch population (49.2% male; 50.2% female) and the road-active population (56.4% male; 41.2% female). The category ”Other / prefer not to say” is also substantially larger in the survey (7.2%) than in the benchmarks, which may reflect differences in response-option framing and survey-mode effects.

The most pronounced deviations are visible in age and education. Respondents aged 25- 34 comprise 46.1% of the sample, compared with 16.3% in the Dutch population and 21.2% in the road-active population. Conversely, older adults are underrepresented, particularly the 65+ group (0.6% in the sample versus 26.0% in the Dutch population and 11.9% in the road-active population). Education is similarly shifted upwards: 45.0% of respondents report a university Master’s degree or higher, compared with 14.7% in the Dutch population and 18.2% in the road-active population. Lower and intermediate education groups are correspondingly underrepresented, most notably vocational education (MBO: 9.4% in the sample versus 36.7% and 34.1% in the Dutch and road-active populations, respectively). These skewnesses should be taken into account when interpreting descriptive choice shares and behavioural patterns, particularly in analyses where education and age are expected to correlate with flexibility, WFH feasibility, or mode preferences.

More specifically, these sample distortions should be considered mainly when interpreting how far the descriptive patterns in this sample can be generalised to broader populations. Because the sample is skewed toward younger, highly educated respondents, the observed choice shares and subgroup distributions should not be interpreted as population estimates for Dutch commuters more generally. This is particularly relevant for analyses in which age, education, or regional context may be related to differences in flexibility, WFH feasibility, or mode preferences. The benchmarking results therefore mainly qualify the transferability of descriptive outcomes and subgroup prevalence, while the observed behavioural patterns remain informative for interpreting the empirical results within the sample.

Mobility-related characteristics align somewhat more closely with the road-active benchmark than with the general population, but differences remain. Licence ownership is high in the sample (78.3%), although it remains below both benchmarks (83.2% in the Dutch population and 96.5% in the road-active population). Spatially, the sample is concentrated in the Randstad (59.4%), exceeding both the Dutch population (51.0%) and the road-active population (44.5%). Finally, the distribution of working days suggests a bias toward full-time or near-full-time employment: respondents working five days per week account for 60.0% of the sample, closely matching the road-active share (58.2%) but exceeding the Dutch benchmark (48.5%). Part-time schedules of three days or fewer are underrepresented relative to the Dutch population.

The benchmarking results are based on the final analytical sample. Two additional respondents were excluded after the main cleaning steps because they did not report their main commuting mode, which is required to construct commuting-context descriptives and to define mode-specific subsamples used later in the analysis.

Taken together, the benchmarking results imply that the survey best represents younger, highly educated, Randstad-based working commuters. This is consistent with the recruitment channels and with the behavioural focus on commuting adaptations. In the remainder of this chapter, descriptive statistics are therefore presented for both the full cleaned sample (relevant to the SC component) and, where appropriate, for the car-commuter subsample that received the pivot and RP modules.

Table 5.2: Sample composition benchmarked against the Dutch population and the road-active population (N = 180).

Category	Sample (%)	Dutch population (%)	Road-active population (%)
Gender			
Male	61.1	49.2	56.4
Female	31.7	50.2	41.2
Other / prefer not to say	7.2	0.6	2.4
Age			
18–24	15.0	10.2	8.4
25–34	46.1	16.3	21.2
35–44	18.9	15.4	20.8
45–54	9.4	15.1	19.5
55–64	10.0	17.0	18.2
65+	0.6	26.0	11.9
Education			
University MSc or higher	45.0	14.7	18.2
HBO	28.3	15.9	22.5
University BSc	12.2	6.5	8.4
Vocational (MBO)	9.4	36.7	34.1
Secondary / primary / none	5.0	10.7	16.8
Driving licence			
Yes	78.3	83.2	96.5
No	21.7	16.8	3.5
Residence			
Randstad	59.4	51.0	44.5
Not Randstad	40.6	49.0	55.5
Working days per week			
5 days	60.0	48.5	58.2
4 days	27.8	19.1	24.1
3 days	5.6	14.8	10.2
2 days	5.0	8.0	4.5
1 day	1.7	9.6	3.0

Several work-organisation items have $N = 158$ because they were asked only to respondents who indicated that WFH is feasible to some extent; respondents who reported that WFH is not possible did not receive these follow-up questions.

Table 5.3: Work organisation, WFH, and commuting context in the cleaned sample.

Question	N	(%)
Ability to WFH ($N = 180$)		
Yes, almost always (not location-bound)	77	42.8
Yes, but only limited	81	45.0
No, not possible	22	12.2
Main commute mode (normal workday) ($N = 180$)		
Car	81	45.0
Public transport	49	27.2
Walk/Bike	50	27.8
Employer reimburses commute costs ($N = 180$)		
Yes	127	70.6
No	53	29.4
Flexibility of working hours/location ($N = 158$)		
Yes, largely flexible	87	55.1
Somewhat flexible	65	41.1
No, fixed hours & location	6	3.8
Fixed office days / on-site obligations ($N = 158$)		
No fixed days	50	31.6
Yes, 1 day/week	51	32.3
Yes, 2 days/week	32	20.3
Yes, 3 days/week	15	9.5
Yes, 4 days/week	10	6.3
Yes, 5 days/week	0	0.0
Allowed WFH days per week ($N = 158$)		
1 day/week	16	10.1
2 days/week	43	27.2
3 days/week	40	25.3
4 days/week	27	17.1
5 days/week	32	20.3
Actual average WFH days per week ($N = 158$)		
0 days/week	29	18.4
1 day/week	60	38.0
2 days/week	46	29.1
3 days/week	20	12.7
4 days/week	2	1.3
5 days/week	1	0.6
Lease car (car commuters only) ($N = 81$)		
No	51	63.0
Yes	30	37.0
Access mode to public transport (PT commuters only) ($N = 49$)		
Bike	29	59.2
Walk	18	36.7
Car	2	4.1
Car available if needed (PT commuters only) ($N = 49$)		
No	36	73.5
Yes	13	26.5

5.3. Working and commuter characteristics

This section summarises key working arrangements and commuting context in the cleaned analytical sample, with a focus on variables most relevant to interpreting behavioural adaptation in the stated choice (SC) and pivot components.

A first salient pattern concerns WFH feasibility. A large majority of respondents indicate that working from home is feasible in some form: 45.0% report that WFH is possible but only in a limited way, and 42.8% report that it is almost always possible. Only a relatively small share (12.2%) indicates that WFH is not possible. This distribution suggests that the sample contains a substantial group with meaningful flexibility in work location, which is important because WFH directly competes with travel as an adjustment mechanism under disruptive commuting conditions.

Commuting modes reflect a commuter-oriented sample with a strong car component, but not exclusively car-based. The car is the most common mode of commuting (45.0%), followed by public transport (27.2%) and walking/cycling (27.8%). The non-car shares are substantial, which indicates that the data capture a broader commuting context than car-only travel. For later interpretation, this implies that baseline habits and constraints differ markedly across respondents, particularly regarding the feasibility of switching modes versus switching to WFH.

Workplace and schedule constraints show a mixed picture of flexibility. Employer reimbursement of commuting costs is common (70.6%), which may reduce the perceived marginal cost of commuting for many respondents and potentially dampen cost-driven behavioural responses. At the same time, a majority of respondents report flexibility in working hours and/or location (55.1% largely flexible; 41.1% somewhat flexible), with only a small minority indicating fixed hours and location (3.8%). This reinforces the interpretation that the sample is characterised by comparatively high levels of workplace flexibility.

Despite this flexibility, fixed on-site obligations remain prevalent. Among respondents with valid responses to the on-site obligation question, roughly two-thirds report at least one fixed office day per week, with the highest shares at one day (32.3%) and no fixed days (31.6%). Higher-frequency on-site requirements are less common, and four or more fixed days per week together represent a small minority. This combination—high WFH feasibility and time flexibility, yet a non-trivial presence of fixed on-site obligations—suggests that, for many respondents, WFH is feasible but not unconstrained. In practice, this matters because disruptions may trigger WFH substitution for some trips, while others remain ”non-negotiable” due to mandatory on-site presence.

The reported WFH intensity aligns with the feasibility profile. Most respondents report 1–2 days of working from home per week on average (38.0% and 29.1%, respectively), while 0 days (18.4%) and 3 or more days (14.6% combined) are less common. This indicates that WFH, when available, is typically used as a partial rather than a full replacement for commuting, which is consistent with hybrid work arrangements.

Finally, subsample-specific indicators provide further context on commuter constraints. Within car commuters ($N = 81$), 37.0% report access to a leased car, implying that a sizable minority may face different marginal commuting costs or stronger car-oriented commitments. Among public transport commuters ($N = 49$), the most common modes are bicycle (59.2%) and on foot (36.7%), with car access to the station rare (4.1%). Moreover, most public transport commuters report that no car is available when needed (73.5%), suggesting that mode substitution to a car may be infeasible for a large share of this group. These asymmetries in resource availability and constraints should be kept in mind when interpreting stated responses to disruption scenarios: flexibility is not only a matter of preferences, but also of access and feasible choice sets.

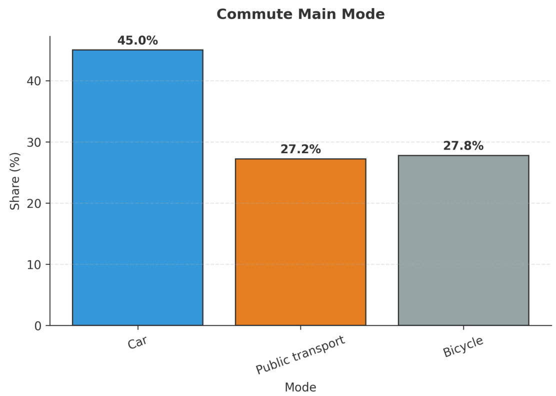
Overall, the descriptive patterns indicate a sample with relatively high workplace flexibility and widespread WFH feasibility, while commuting remains heterogeneous across mode groups, with meaningful constraints on substitution, particularly for public transport commuters without access to a car. These characteristics provide an important backdrop for the behavioural results presented in subsequent chapters.

5.4. Travel choices

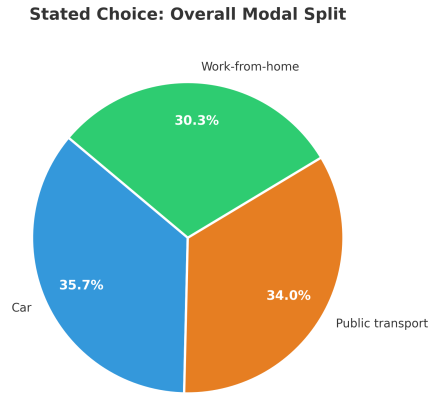
This section describes the key travel-choice patterns observed in the stated choice experiment, the pivot task, and the revealed-preference module.

5.4.1. Baseline context and SC choice distribution

Figure 5.1a summarises the respondents' reported main commuting mode on a normal workday. This provides context for interpreting stated choices, as baseline commuting habits are likely to shape which behavioural adjustments are perceived as feasible.



(a) Main commute mode.



(b) Stated choice: overall choice shares.

Figure 5.1: Baseline commute mode and overall stated choice shares.

Across all SC tasks, the overall choice shares are relatively balanced between the three alternatives (Figure 5.1b). This indicates that the experimental design successfully generates variation in stated decisions, rather than collapsing into a single dominant alternative. In other words, respondents meaningfully trade off between driving, public transport, and working from home under the presented conditions.

5.4.2. SC choices by WFH feasibility

WFH feasibility is a central moderator of behavioural adaptation in this study. Figure 5.2 compares the chosen alternatives for respondents who cannot work from home versus those who can. The contrast is intuitive: respondents without WFH-feasibility shift choice mass away from the work-from-home alternative and reallocate it primarily toward the remaining travel modes. This segmentation supports the interpretation that the WFH alternative is not merely a stated "preference" but reflects a real constraint in the respondent's choice set.

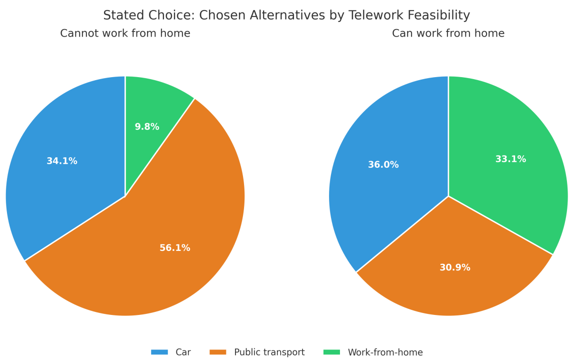


Figure 5.2: Stated choice: chosen alternatives by WFH feasibility (can vs cannot work from home).

5.4.3. Switching behaviour in the SC experiment

Beyond aggregate choice shares, it is informative to assess the consistency with which respondents select the same alternative across the SC tasks. Figure 5.3 classifies respondents by the number of unique alternatives they selected during the SC experiment. A relatively small share always chooses a single option, while the majority select either two or all three alternatives at least once. This pattern indicates substantial within-person switching across scenarios, consistent with respondents responding to attribute changes rather than adhering to a fixed ”always car” or ”always PT” heuristic. The distribution provides a useful quality check that the SC tasks induce meaningful behavioural variation.

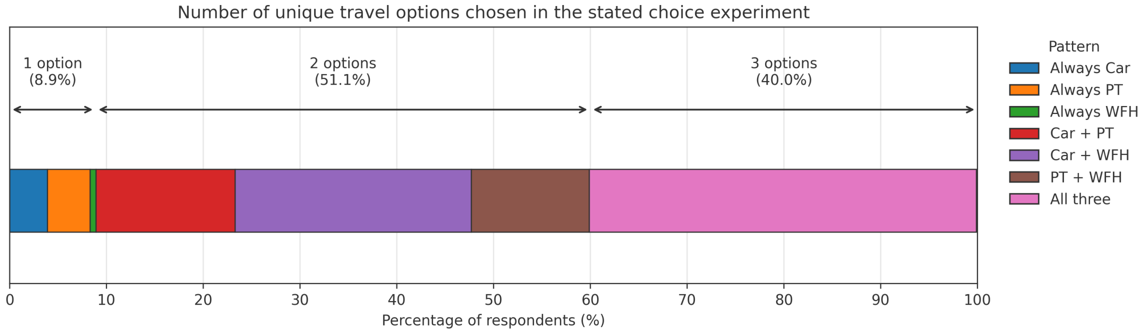


Figure 5.3: Switching behaviour in the stated choice experiment: number of unique alternatives chosen per respondent.

6
Results

This chapter presents the empirical results and interprets the key behavioural mechanisms underlying commuters' adaptation to planned roadworks. The aim is twofold: to document robust empirical patterns in stated and revealed behaviour, and to translate the estimated model outcomes into evidence that will be used to answer the research questions in Chapter 7. Accordingly, this chapter combines model estimates with a focused discussion of the results' implications, explicitly relating the main findings to the relevant literature.

6.1. SC MNL model

Before proceeding to the final parameter estimates, several model specifications are evaluated to ensure that the benchmark effectively captures the structural differences between travel and non-travel alternatives. This iterative selection process, based on statistical fit and behavioural plausibility, establishes the foundation for interpreting the population-level sensitivities and subsequent heterogeneity analyses.

6.1.1. SC attributes to utilities

Based on the SC questionnaire, the initial specification includes: car travel time and cost, PT travel time, WFH on-site obligation, and peak context. The resulting panel MNL utilities are:

$$
\begin{aligned}
V_{\text{car}} &= \beta_{\text{time,car}} \cdot X_{\text{time,car}} + \beta_{\text{cost,car}} \cdot X_{\text{cost,car}} && (6.1)\\
V_{\text{pt}} &= ASC_{\text{pt}} + \beta_{\text{time,pt}} \cdot X_{\text{time,pt}} && (6.2)\\
V_{\text{wfh}} &= ASC_{\text{wfh}} + \beta_{\text{on-site,med}} \cdot D_{\text{on-site,med}} + \beta_{\text{on-site,high}} \cdot D_{\text{on-site,high}} \\
&\quad + \beta_{\text{peak,med}} \cdot D_{\text{peak,med}} + \beta_{\text{peak,high}} \cdot D_{\text{peak,high}} && (6.3)
\end{aligned}
$$

The car is the reference alternative (no Alternative-specific constant (ASC)), whereas PT and WFH include ASCs to capture systematic utility components not captured by the limited SC attribute set. Time and cost are scaled for interpretability (time in 10-minute increments; car cost per €10). A panel likelihood is used because each respondent completed multiple SC tasks; robust standard errors are reported to remain conservative with respect to within-person correlation and remaining heteroscedasticity.

PT cost is excluded because it is held constant in the SC experiment and is therefore not separately identifiable from the PT constant in this design.

6.1.2. Specifications and model comparison

The benchmark specification is developed in a structured way. Starting from the design-consistent SC_MNL_Start model (Section 6.1.1), a limited set of additional specifications is estimated to test three substantive questions relevant to both interpretation and subsequent heterogeneity modelling.

First, WFH is structurally different from travel alternatives. Unlike car and PT, WFH is not universally feasible and depends on job and employer constraints. As a result, the WFH constant may combine preferences with feasibility if feasibility is not modelled explicitly. Therefore, an explicit WFH feasibility term is tested as a conceptually motivated extension.

Second, regional context may shift baseline PT propensity. In the Netherlands, PT accessibility and service quality may differ between the Randstad and non-Randstad areas. Areas outside the Randstad are more widely dispersed and therefore rely more on the car, implying a potential baseline shift in PT that is not captured by PT travel time alone (Kennisinstituut voor Mobiliteitsbeleid (KiM), 2022). A Randstad shift on the PT constant is therefore tested as a targeted contextual hypothesis. The same shift is also tested, conditional on WFH feasibility, to assess whether a better representation of WFH affects the allocation of baseline utility across alternatives.

Third, observed heterogeneity may explain part of the large baseline components. The benchmark models contain sizeable alternative-specific constants, which may indicate systematic differences between respondents beyond the attributes included in the SC tasks. To assess whether such differences are plausibly related to observed socio-demographic and job-context characteristics, diagnostic specifications are estimated with a targeted Observed Heterogeneity model. This diagnostic is not intended to replace the benchmark; its purpose is to indicate whether heterogeneity is present and which dimensions appear most relevant, thereby motivating subsequent mixed logit and Latent Class modelling (Hensher et al., 2005; Train, 2008).

Across all candidate models, the key selection principle is that parsimony parameters are retained for the benchmark only if they are behaviourally interpretable and improve penalised fit (AIC/BIC), rather than improving log-likelihood alone at the expense of model interpretability. Table 6.1 summarises the candidate specifications and their fit.

Table 6.1: Candidate panel MNL specifications for the SC experiment. Lower AIC/BIC indicates a preferred fit after penalising model complexity.

Model specification	k	Final LL	AIC	BIC
SC_MNL_Start (SC attributes incl. PEAK in WFH)	9	-901.19	1820.39	1849.12
SC_BASE (PEAK removed)	7	-901.84	1817.68	1840.03
SC_BASE + WFH feasibility	8	-877.65	1771.30	1796.84
SC_BASE + Randstad shift in PT	8	-901.75	1819.50	1845.04
SC_BASE + WFH feasibility + Randstad shift in PT	9	-877.57	1773.15	1801.88
SC_BASE + Observed Heterogeneity	22	-829.34	1702.68	1772.92

The benchmark MNL specification is developed systematically. The full set of candidate specifications and the corresponding model comparison are reported in Appendix G. Based on penalised fit (AIC/BIC) and behavioural interpretability, the benchmark panel MNL used for interpretation and as the reference point for heterogeneity modelling is *SC_BASE + WFH feasibility*. This benchmark is used to establish average population sensitivities before introducing unobserved heterogeneity in the Mixed Logit and Latent Class analyses (Hensher et al., 2005; Train, 2008).

6.1.3. MNL model results

Table 6.2 reports the robust parameter estimates for the benchmark specification.

Delay as the main trigger of adaptation

The central result of the benchmark MNL model is that increased car travel time significantly reduces the attractiveness of continued car commuting. The coefficient for car travel time is negative and precisely estimated ($\beta_{\text{Time, Car}} = -0.97$, $p < 0.001$), indicating that disruption severity, operationalised here as additional delay, is a key trigger of behavioural adaptation. As the delay increases, the probability of continuing by car declines, while substitution towards PT and WFH becomes more likely. This identifies delay as the main behavioural pressure in the SC model, although the alternative that absorbs this response depends strongly on commuter constraints.

Table 6.2: Benchmark panel MNL (SC_BASE + WFH feasibility): robust parameter estimates. Time is scaled per 10 minutes; car cost per €10.

Parameter	Estimate	Rob. SE	t-stat	p-value
ASC_{WFH}	-9.33	1.06	-8.76	< 0.001
ASC_{PT}	-7.65	1.47	-5.21	< 0.001
$\beta_{\text{Cost, Car}}$	-2.41	0.48	-5.00	< 0.001
$\beta_{\text{Time, Car}}$	-0.97	0.09	-10.50	< 0.001
$\beta_{\text{Time, PT}}$	-0.16	0.15	-1.05	0.294
$\beta_{\text{on-site, Medium}}$	-1.63	0.19	-8.81	< 0.001
$\beta_{\text{on-site, High}}$	-3.70	0.48	-7.64	< 0.001
$\delta_{\text{WFH, Feasible}}$	1.92	0.48	4.00	< 0.001

Baseline sensitivity to delay

To translate the estimated utility parameters into behavioural insights, Figure 6.1 presents a baseline simulation of mode choice probabilities under increasing delay conditions.

The simulation relies on a reference trip based on sample averages: a base-car travel time of 41 minutes, a fuel cost of €8.00, and a public-transport door-to-door time of 55 minutes. The commuter profile assumes that WFH is feasible and that on-site obligations are present, but not required.

The results illustrate the substitution pattern for this representative commuter. As the delay increases, the probability of choosing the car declines. For this average profile with medium on-site obligations, the model predicts that public transport is slightly preferred over working from home. This is driven by the negative utility penalty associated with on-site obligations ($\beta_{\text{on-site, Medium}} = -1.63$), which suppresses the attractiveness of WFH relative to PT. However, the absolute probability of switching to either alternative remains relatively low, reflecting the strong baseline preference for the car.

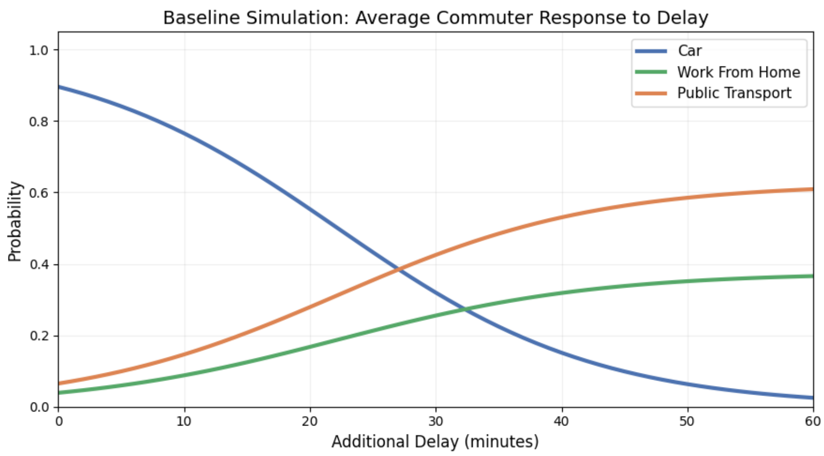


Figure 6.1: Baseline simulation: Predicted probability of mode choice under increasing delay for an average commuter (Car base time: 41 min; Cost: €8.00; WFH feasible).

The determining role of constraints

A crucial finding of the MNL analysis is that aggregate sensitivity to delay masks significant structural heterogeneity in job constraints. Figure 6.2 isolates the probability of choosing the car for two distinct commuter profiles to demonstrate this ”lock-in” effect.

The ”Flexible Worker” (solid line) represents a commuter for whom WFH is feasible and on-site obligations are low. The ”Fixed Worker” (dashed line) represents a commuter for whom WFH is not feasible and on-site obligations are high.

The visual comparison reveals a stark dichotomy. The flexible worker exhibits high elasticity, abandoning the car rapidly once delays exceed approximately 15 minutes. In contrast, the fixed worker exhibits significant inertia. For this group, the probability of driving remains high even under severe delay conditions. This confirms that the observed car dependence is not solely a preference for driving, but is structurally enforced by job constraints that render the primary substitute unavailable.

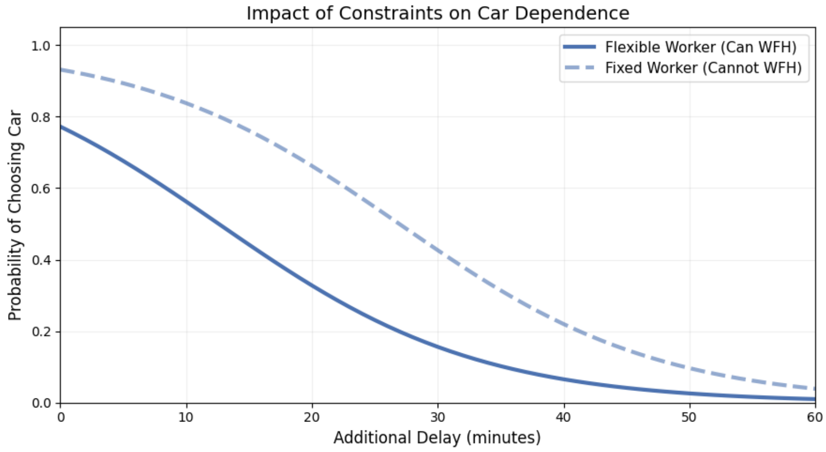


Figure 6.2: Impact of constraints: Probability of choosing the car for a Flexible Worker (Low obligations, WFH feasible) versus a Fixed Worker (High obligations, WFH not feasible).

Scenario analysis: Delay sensitivity versus employer constraints

To contextualise the magnitude of the estimated parameters, Figure 6.3 compares the relative impact of travel time (represented by delay) with that of employer constraints (represented by on-site obligations). The simulation assumes a commuter who can WFH.

The results reveal a significant disparity in both the baseline probability and the tipping point for behavioural change.

Commuters with strict on-site obligations exhibit strong inertia. The curve remains high (>0.9) for small to moderate delays, indicating a tolerance buffer. A substantial decline in car use occurs only under extreme delay conditions (>30 minutes), likely reflecting a shift to public transport rather than WFH.

In contrast, reducing on-site obligations triggers a much earlier and sharper response. The starting probability is lower, and the curve steepens rapidly. The tipping point for this group occurs significantly earlier (approximately 15 minutes of delay), indicating that flexible employer policies lower the threshold for switching away from the car.

This comparison demonstrates that employer obligations determine the *resilience* of car commuting. High obligations delay the behavioural response, forcing commuters to absorb substantial utility losses before switching, whereas low obligations allow for a more immediate adaptation to traffic disruptions.

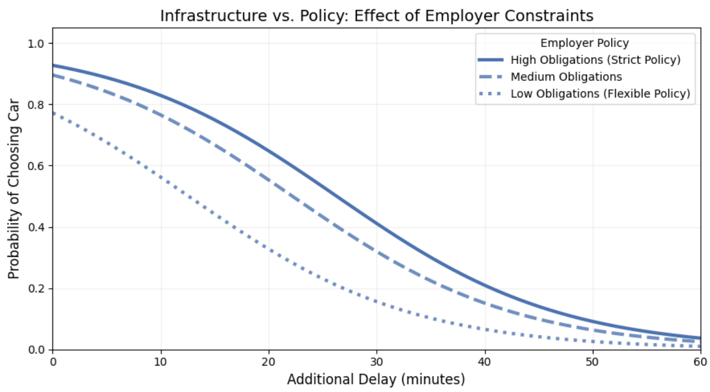


Figure 6.3: Sensitivity analysis: Predicted probability of choosing the car under increasing delay for three levels of employer-imposed on-site obligations (Low, Medium, High).

Working from home as constraint-driven adaptation

WFH is primarily driven by constraints rather than by travel attributes alone. The coefficients for on-site obligations are large, monotonic, and negative ($\beta_{\text{on-site, High}} = -3.70$), while the feasibility indicator is positive and significant ($\delta_{\text{WFH, Feasible}} = 1.92$). This confirms that WFH is not universally available and that its utility depends strongly on employer- and job-related constraints captured by on-site obligations and feasibility. The simulations therefore suggest that delay creates the pressure to adapt, but that WFH absorbs this response only when the work situation allows it.

PT switching dominated by baseline barriers

The coefficient for PT travel time is negative but not statistically significant ($p = 0.294$), while the PT constant is large and negative ($ASC_{\text{PT}} = -7.65$). For this sample of predominantly car commuters, this indicates that switching to PT is driven less by marginal changes in PT travel time and more by baseline preferences or barriers. This motivates the subsequent heterogeneity analysis to assess whether subgroups display distinct sensitivities that are masked by the population average.

Average time cost trade-off and implied Value of Time (VOT)

Car travel time and car cost are both negative and precisely estimated ($t = -10.50$ and $t = -5.00$, respectively), confirming that respondents trade off higher travel time and monetary costs against alternative choices. The ratio of the time-to-cost coefficients yields the implied Value of Time (VOT). Using the scaling factors (time per 10 minutes, cost per €10), the VOT is calculated as:

$$\text{VOT} = \frac{|\beta_{\text{time,car}}|}{|\beta_{\text{cost,car}}|} \cdot \frac{10\,€}{10\,\text{min}} \approx \frac{0.97}{2.41} \cdot 1 \approx 0.40\,€/\text{min} \approx 24\,€/\text{hour}. \tag{6.4}$$

6.2. SC Mixed Logit Analysis

The Multinomial Logit (MNL) benchmark presented in the previous section assumes homogeneity, meaning that all respondents share identical sensitivities to time, cost, and WFH. However, individual behaviour in commuting is likely more diverse. In particular, the intrinsic preference for working from home may vary due to unobserved factors such as home-office quality, household composition, or job autonomy.

To explicitly model this variation, a Mixed Logit (MXL) model is estimated. Unlike the MNL, which estimates a single fixed parameter for the population, the MXL estimates a distribution of parameters (defined by a mean μ and a standard deviation σ). This enables quantification of unobserved heterogeneity. Consistent with the modelling strategy, socio-demographic covariates are excluded at this stage to obtain a clean estimate of parameter distributions; the explanation of heterogeneity using observable profiles is reserved for the Latent Class Analysis in Section 6.3.

6.2.1. Model specification and selection

To determine the optimal heterogeneity structure, a stepwise specification search was conducted. The selection of random parameters was guided by transport economic theory and the specific research questions regarding WFH. Five models were estimated to assess the randomness of the sensitivity to Car Time, Car Cost, and baseline WFH preference.

Car travel time sensitivity is a fundamental concept in transport economics. Commuters differ in their time sensitivity due to scheduling constraints, comfort preferences, or the ability to multitask (Hess et al., 2005; Small, 2012). Capturing this heterogeneity is essential to avoid forecasting bias, as ignoring it forces a single trade-off ratio on the entire population.

Similarly, sensitivity to Car Cost is expected to vary, primarily due to differences in income and budget constraints. Theoretically, cost sensitivity should be strictly negative; therefore, a negative log-normal distribution is tested to ensure behavioural consistency while allowing for scale differences between high- and low-income groups.

Finally, the potential for WFH is not solely determined by objective constraints (which are controlled for by the feasibility and on-site attributes) but also by intrinsic attitudes and unobserved job characteristics. Randomising the alternative-specific constant for WFH allows the model to capture this unobserved ”WFH-perception”.

Table 6.3 summarises the model fit statistics. The results demonstrate that introducing heterogeneity substantially improves model fit relative to the fixed-parameter benchmark. The choice for the MXL 4 specification is reported in Appendix H.

Table 6.3: Comparison of Mixed Logit specifications. all models were estimated using 1,000 Halton draws.

Model Specification	Random Parameters	LL	AIC	BIC
MNL Benchmark	None	-877.65	1771.31	1796.85
MXL 1	Time	-791.29	1600.57	1629.31
MXL 2	Cost	-791.20	1600.40	1629.14
MXL 3	WFH	-833.68	1685.36	1714.10
MXL 4	**Time + WFH**	**-747.86**	**1515.71**	**1547.64**
MXL 5	Time + Cost + WFH	-743.09	1508.18	1543.30

6.2.2. MXL model results

Table 6.4 reports the parameter estimates for the preferred MXL 4 model. The fixed parameters align with the benchmark MNL results: on-site obligations exert a strong negative effect on WFH utility, while feasibility has a positive effect. The main contribution of the MXL is the identification of unobserved heterogeneity in car travel time sensitivity and baseline WFH preference.

Table 6.4: Parameter estimates for the preferred Mixed Logit model (MXL 4). Random parameters are defined by a mean (μ) and standard deviation (σ).

Parameter	Estimate	Rob. SE	t-stat	p-value
Random Parameters				
$\mu_{\text{Time,Car}}$	-2.13	0.24	-8.92	< 0.001
$\sigma_{\text{Time,Car}}$	0.50	0.06	8.70	< 0.001
$\mu_{\text{ASC,WFH}}$	-18.62	2.00	-9.30	< 0.001
$\sigma_{\text{ASC,WFH}}$	2.11	0.28	7.47	< 0.001
Fixed Parameters				
$\beta_{\text{Cost,Car}}$	-4.50	0.82	-5.46	< 0.001
ASC_{PT}	-15.62	2.62	-5.96	< 0.001
$\beta_{\text{time,pt}}$	-0.29	0.24	-1.18	0.238
$\beta_{\text{on-site, Medium}}$	-2.72	0.36	-7.57	< 0.001
$\beta_{\text{on-site, High}}$	-5.72	0.63	-9.15	< 0.001
$\delta_{\text{WFH,possible}}$	3.26	0.77	4.25	< 0.001

Significant heterogeneity in time sensitivity and baseline WFH preference

The standard deviation for car travel time sensitivity is highly significant ($\sigma_{\text{Time, Car}} = 0.50$), indicating that while travel time is disliked on average (negative mean), the intensity of this dislike varies across respondents. This supports the interpretation that a single population-average trade-off is an oversimplification and motivates segmentation in the subsequent LC analysis.

Heterogeneity in baseline WFH preference is even more pronounced ($\sigma_{\text{ASC,WFH}} = 2.11$). This implies that, even after controlling for feasibility and on-site obligations, the intrinsic attractiveness of working from home varies substantially across individuals.

6.2.3. Interpreting the heterogeneity patterns

Figure 6.4 visualises the estimated distributions for the two random parameters and clarifies how the MXL extends the benchmark MNL. The key insight is that heterogeneity differs strongly across behavioural dimensions.

First, heterogeneity in car time sensitivity is statistically significant but relatively concentrated: the distribution is centred on a negative mean and shows a moderate spread. This indicates that commuters consistently dislike additional travel time, yet the intensity of that disutility varies across individuals. In practical terms, this implies that the impacts of disruption are not uniform: a subgroup experiences relatively large welfare losses from additional delay, whereas others are more tolerant.

Second, baseline WFH preferences exhibit substantially greater dispersion. Even after controlling for objective constraints (feasibility and on-site obligations), the WFH constant varies widely across respondents. This indicates that WFH adaptation is not explained solely by constraints; it is also shaped by unobserved attitudes and job-specific factors. As a result, the population-average WFH effect in the benchmark MNL masks meaningful behavioural differences in the propensity to avoid commuting by WFH.

Taken together, the MXL results suggest that heterogeneity is not only present but also structured along interpretable dimensions (time pressure and baseline WFH propensity). This motivates the Latent Class framework presented in the next section, which translates these continuous variations into distinct behavioural segments and relates these segments to observable characteristics.

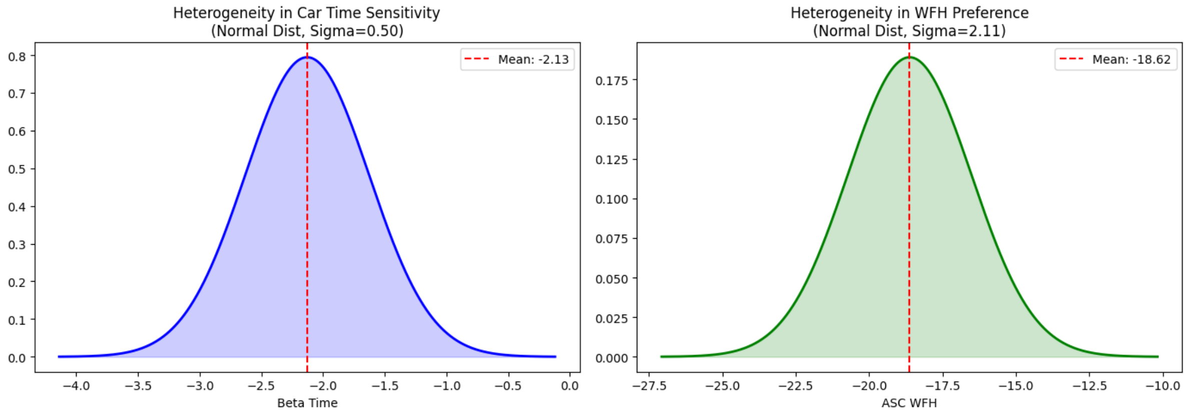


Figure 6.4: Estimated heterogeneity distributions derived from MXL 4. Left: Car Time Sensitivity (Normal). Right: WFH Preference (Normal).

6.3. Latent Class analysis

The Mixed Logit analysis (Section 6.2) established significant unobserved heterogeneity in car travel time sensitivity and baseline WFH preference. While the MXL model represents this variation as continuous distributions, the results also raise a more substantive question: whether commuters can be grouped into distinct behavioural segments that differ in their responses to disruption severity. This is relevant to the research question because the previous models already suggested that adaptation is not uniform across respondents. Some commuters appear to respond relatively quickly to additional delay, whereas others remain more persistent in car use or differ in their baseline propensity to use WFH. To translate this heterogeneity into interpretable groups and relate them to observable characteristics, a Latent Class model is estimated.

6.3.1. Model selection overview

To translate the heterogeneity identified in the Mixed Logit model into interpretable behavioural segments, several Latent Class specifications were estimated. The candidate set varies along two dimensions: the number of classes ($K \in \{2, 3\}$), and whether class membership is explained using covariates. In addition, an alternative two-class specification with a richer class-specific utility structure was tested as a robustness check.

This step is not included solely for modelling complexity. The aim is to assess whether the heterogeneity observed in the MXL results can be summarised into a limited number of behaviourally meaningful groups that differ in their delay response and baseline adaptation tendency. If such groups exist, the LC model provides a more interpretable representation of heterogeneity than a purely continuous specification and enables the relation of behavioural differences to observable socio-demographic profiles.

Table 6.5 summarises the fit of the candidate models. The detailed selection rationale and the argumentation for the preferred benchmark specification are reported in Appendix I.

Table 6.5: Model selection for the Latent Class analysis.

Model Specification	Classes	Covariates	LL	BIC
LC3 (Constants only)	3	No	-762.62	1597.95
LC3 (With Covariates)	3	Yes	-741.49	1576.46
LC2 (Extended Parameters)	2	Yes	-785.72	1649.34
LC2 (Parsimonious)	**2**	**Yes**	**-785.71**	**1644.11**

6.3.2. Benchmark specification and role in the modelling pipeline

A structured selection process was followed to determine the number of classes and the preferred LC specification. The full set of candidate LC models and the selection rationale are reported in Appendix I. Based on interpretability and robustness, the benchmark model for interpretation is a parsimonious two-class specification (LC2), in which heterogeneity is restricted to the two dimensions identified in MXL 4 (car time sensitivity and baseline WFH preference).

Within the modelling pipeline, the role of the LC model is not only to improve fit but also to clarify whether the average delay response masks distinct behavioural segments with different adaptation logics. In that sense, the LC model complements Mixed Logit analysis by making heterogeneity more interpretable and linking segment membership to observable respondent characteristics.

6.3.3. Estimation results and behavioural interpretation

The benchmark LC2 model identifies two distinct segments of comparable size, with class 1 (49.8%) and class 2 (50.2%). Table 6.6 reports the class-specific parameters and the class membership model.

Table 6.6: Estimation results for the preferred two-class model (LC2).

Parameter	Estimate	Rob. SE	t-stat	Sig.
Class 1: Delay-sensitive / lower WFH propensity				
ASC_{WFH}	-13.08	1.33	-9.87	***
$\beta_{\text{Time,Car}}$	-1.77	0.19	-9.18	***
Class 2: Delay-tolerant / higher WFH propensity				
ASC_{WFH}	-11.08	1.57	-7.08	***
$\beta_{\text{Time,Car}}$	-1.13	0.16	-6.99	***
Generic parameters				
ASC_{PT}	-10.47	1.96	-5.36	***
$\beta_{\text{Cost,Car}}$	-2.73	0.59	-4.61	***
$\beta_{\text{on-site, Medium}}$	-1.69	0.20	-8.39	***
$\beta_{\text{on-site, High}}$	-3.43	0.46	-7.53	***
$\delta_{\text{WFH,Pos}}$	1.89	0.50	3.76	***
Class membership (Ref: Class 1)				
Constant	-4.33	1.43	-3.04	**
Age (per 10 years)	0.90	0.32	2.82	**
High Education (Dummy)	1.68	0.75	2.24	*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Class-specific behavioural logic

Class 1 is characterised by higher car time sensitivity ($\beta_{\text{Time,Car}} = -1.77$) and a lower baseline propensity for WFH ($ASC_{\text{WFH}} = -13.08$) than Class 2 (Table 6.6). Consistent with this ordering, Figure 6.5 shows that the predicted car-choice probability declines faster for Class 1 as delay increases. This indicates a segment for whom additional delay is more behaviourally binding in the simulated setting, even though WFH remains relatively unattractive in baseline terms.

In contrast, Class 2 is less time-sensitive ($\beta_{\text{Time,Car}} = -1.13$) and has a higher baseline propensity for WFH ($ASC_{\text{WFH}} = -11.08$). Accordingly, the predicted car-choice probability remains higher over a larger delay range (Figure 6.5), implying greater persistence in car use before switching becomes attractive.

These results add a more segmented interpretation to the previous MXL findings. Rather than suggesting only a smooth distribution of sensitivities, the LC model indicates that the sample can be understood as containing at least two broad behavioural response types: one that reacts more strongly to additional delay and one that remains more tolerant of disruption before adapting.

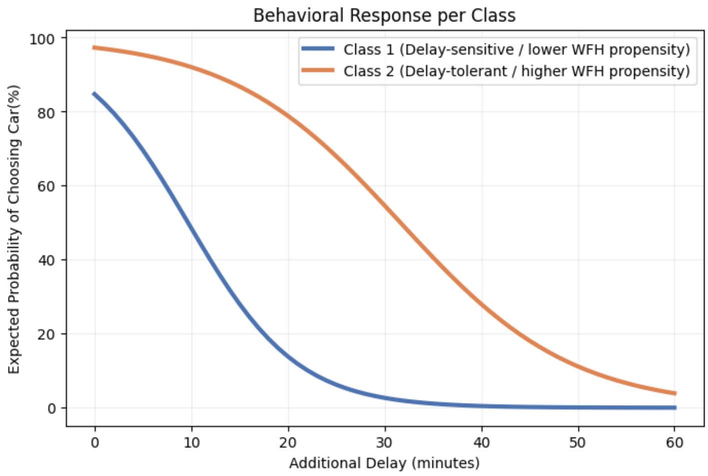


Figure 6.5: Behavioural heterogeneity: Predicted car-choice probability for Class 1 (delay-sensitive / lower WFH propensity) versus Class 2 (delay-tolerant / higher WFH propensity) under identical trip constraints (Base time: 41 min; Cost: €8.00).

Socio-demographic profiling and market response

The class membership model indicates that higher education and age increase the log-odds of membership in Class 2 (Table 6.6). Figure 6.6, therefore, shows a higher predicted car-choice probability for the high-education profile across much of the delay range, reflecting its higher probability of belonging to the more delay-tolerant class. These results imply that aggregate delay sensitivity in this sample is not uniform across socio-demographic profiles, and that differences in persistence arise through both class membership and class-specific sensitivities.

This profiling step is important because it connects the behavioural segmentation back to observable respondent characteristics. As a result, the LC model not only shows that heterogeneity exists, but also suggests how differences in delay response may be distributed across the sample.

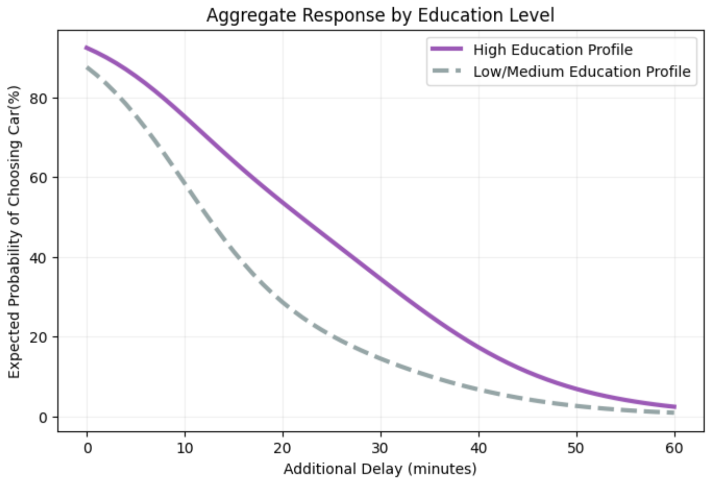


Figure 6.6: Integrated market response: Expected car-choice probability by educational profile at the sample's average age of 35 years, illustrating how socio-demographics affect aggregate delay sensitivity through class membership.

6.4. Pivot experiment results

Complementing the SC experiment, the survey included a pivot module to measure behavioural adaptation to specific disruption scenarios. Unlike the generic SC tasks, the pivot design anchors the hypothetical disruption to the respondent's actual reported car commute, thereby increasing behavioural realism.

Each respondent faced three disruption levels, with their current car travel time increasing by 25%, 45%, and 60%. In each scenario, they chose between continuing by car, switching to public transport (PT), or working from home (WFH). The key metric for analysis is the absolute additional delay in minutes (Δt), which ranges from 1.25 to 72 minutes in the sample (Mean = 18.9 min).

6.4.1. Descriptive trends and switching patterns

Table 6.7 reports the observed aggregate choice shares. These shares should be interpreted as scenario-conditional stated responses from the pivot module among respondents who typically commute by car and had a car available, rather than as population-wide forecasts of realised switching under actual roadworks.

Table 6.7: Observed choice shares by disruption level.

Disruption Level	Car Share	PT Share	WFH Share
Low (25%)	92.6%	0.0%	7.4%
Medium (45%)	53.1%	17.3%	29.6%
High (60%)	29.6%	22.2%	48.1%

The pivot data reveal a strongly non-linear response. At the 25% disruption level, most respondents continue commuting by car, while switching to PT is absent. Between 25% and 45%, car share declines sharply, after which both WFH and PT shares increase further. This pattern suggests a threshold-type response: small delays are largely absorbed, while larger delays trigger substantial adaptation.

6.4.2. Discrete choice modelling approach

To quantify the observed nonlinearity, panel Multinomial Logit (MNL) models were estimated. A detailed overview of the tested functional forms (including linear, log-linear, and percentage-based specifications), fit comparisons, and the stepwise selection procedure is reported in Appendix J.

Based on this analysis, the preferred specification combines a log-linear time term with a tolerance indicator for the low-disruption scenario. Additionally, to better account for constraints on WFH, the model explicitly captures jobs that require physical presence and WFH feasibility.

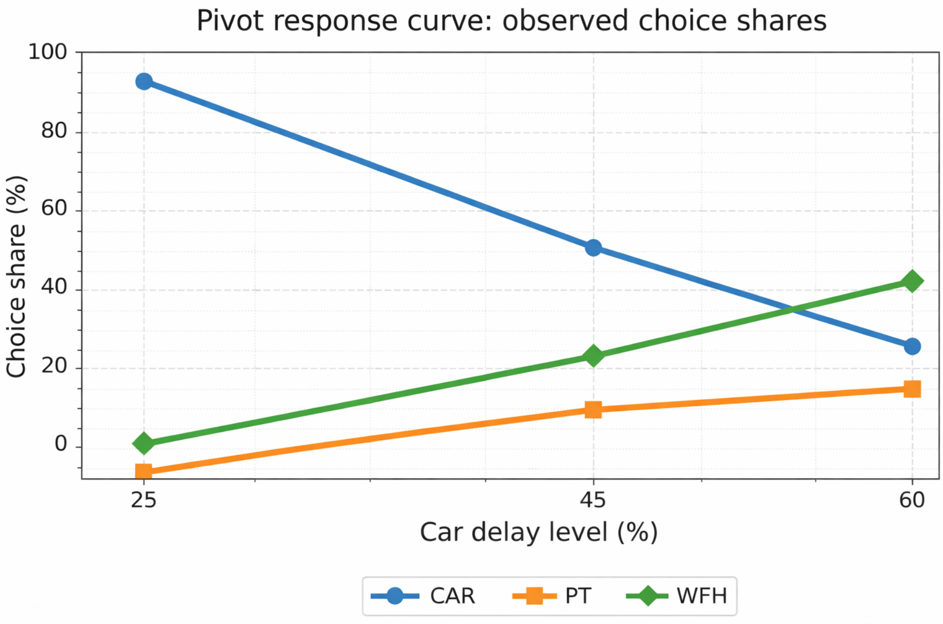


Figure 6.7: Pivot choice shares per severity level

The final utility specification is:

$$U_{\text{car},i} = \beta_{\log} \log(1 + \Delta t_i) + \beta_{\text{Tolerance}}\, D_{\text{LowDelay},i}, \tag{6.5}$$

where $D_{\text{LowDelay}} = 1$ for the 25% disruption scenario and 0 otherwise. Public transport is specified as an ASC-only alternative:

$$U_{\text{pt},i} = ASC_{\text{pt}}. \tag{6.6}$$

WFH utility includes a structural constraint for location-dependent work and a feasibility term:

$$U_{\text{wfh},i} = ASC_{\text{wfh}} + \beta_{\text{Location}}\, \text{MustOnLocation}_i + \beta_{\text{WFH,Feasible}}\, D_{\text{WFH,Feasible},i}. \tag{6.7}$$

6.4.3. Estimation results

Table 6.8 reports the estimation results for the preferred pivot model.

Table 6.8: Pivot MNL estimation results (preferred specification).

Parameter	Estimate	Rob. SE	t-stat	Sig.
ASC_{PT}	-6.50	1.40	-4.65	***
ASC_{WFH}	-5.69	1.51	-3.77	***
$\beta_{\text{Tolerance}}$ (LowDelay)	2.02	0.47	4.29	***
$\beta_{\log}$ (Time sensitivity)	-1.87	0.46	-4.09	***
β_{Location} (Must on Loc)	-3.26	1.16	-2.82	**
$\beta_{\text{WFH, Feasible}}$	2.26	1.05	2.16	*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The tolerance parameter is large and positive ($\beta_{\text{Tolerance}} = 2.02$), indicating substantial inertia in the low-disruption scenario: when the delay is framed as minor (25%), respondents derive additional utility from sticking to their routine, consistent with switching frictions and transaction costs (Cantillo et al., 2007).

Conditional on moving beyond this low-disruption regime, the time sensitivity term is negative and significant ($\beta_{\log} = -1.87$), indicating that larger additional delays reduce the probability of remaining in the car category. The log specification implies that the marginal effect of extra minutes is strongest at smaller Δt and gradually flattens as Δt grows, which is consistent with diminishing marginal sensitivity to very large delays.

Finally, the results highlight the dominance of work-related constraints. The variable indicating that a job must be performed on location is strongly negative ($\beta_{\text{Location}} = -3.26$), implying that for location-bound tasks, switching to WFH is structurally inhibited regardless of traffic conditions. Consistent with this, the WFH feasibility term is positive and significant ($\beta_{\text{WFH, Feasible}} = 2.26$), confirming that the WFH response in the pivot scenarios is primarily governed by whether WFH is feasible in the job context.

6.4.4. Analysis of commuter elasticity and switching thresholds

To move beyond aggregate choice shares, Figure 6.8 visualises commuter elasticity by plotting the probability of switching as a function of absolute additional travel time. By including a baseline (zero delay), the graph captures the ”tipping point” at which commuters shift from routine-based travel to active adaptation.

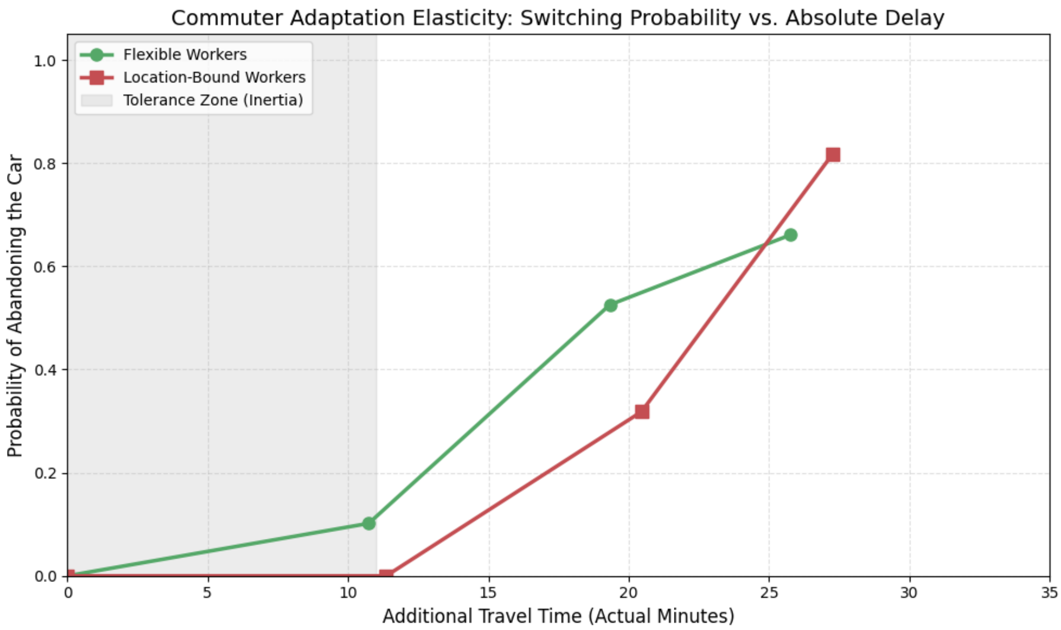


Figure 6.8: Commuter Adaptation Elasticity: The probability of switching to an alternative (PT or WFH) as a function of absolute delay. The shaded area represents the ”Tolerance Zone” where behavioural inertia is dominant.

The analysis reveals a significant ”crossing effect” in the adaptation strategies of different commuter segments:

Figure 6.8 shows the estimated probability of switching away from the car category as additional travel time increases for two commuter segments. In Figure 6.8, the segment labels refer to work-constraint profiles used for the prediction. ”Flexible workers” denote respondents for whom working from home is feasible and who are not required to be physically on location. ”Location-bound workers” denote respondents with binding on-location requirements, for whom WFH is structurally constrained and adaptation, if it occurs, must primarily materialise through travel-based alternatives (notably PT).

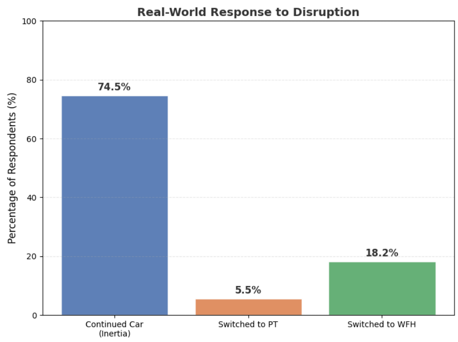
For flexible workers, the switching probability is already non-zero at the first delay within the called tolerance zone and rises sharply between roughly 10 and 20 minutes, after which the curve flattens and reaches approximately 0.66 at 26 minutes. For location-bound workers, switching remains close to zero within the low-delay range and increases primarily as delays approach ≈20 minutes. At the highest average delay point (≈27 minutes), the estimated switching probability for location-bound workers is higher (≈0.82) than for flexible workers (≈0.66), suggesting a crossover at severe disruption levels.

This pattern is consistent with different constraint sets across segments. Flexibility may enable earlier adaptation, whereas on-site requirements may generate stronger inertia at modest delays, followed by a more abrupt change once the disruption becomes sufficiently burdensome. For the location-bound group, adaptation under severe disruption is more likely to occur through travel-based alternatives than through WFH, given that on-site attendance remains required.

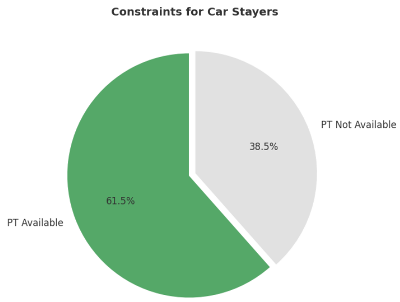
6.5. Revealed Preference analysis

To complement the hypothetical Pivot experiment, the survey included a Revealed Preference (RP) module. Respondents were asked about their actual past experiences with significant delays on their commute. Importantly, this RP question did not elicit the magnitude or duration of the disruption in minutes. Therefore, the RP responses are unconditional with respect to severity and should be interpreted as evidence of realised behavioural inertia and constraint prevalence, rather than as severity-conditioned switching rates comparable to those in the Pivot module.

Among car commuters, 68% reported experiencing a major disruption or delay on their route. Figure 6.9 summarises the reported actions taken during such events and, for those who continued driving, the reported availability of Public Transport.



(a) Observed behavioural response



(b) PT availability for car stayers

Figure 6.9: Revealed Preference results. Left: Actions taken during disruption. Right: Public Transport availability for those who continued driving.

Observed behaviour under disruption

Figure 6.9a shows that 74.5% of respondents reported continuing to commute by car despite the disruption. Among those who changed behaviour, WFH is reported by 18.2% and switching to PT by 5.5%.

For respondents who continued driving, Figure 6.9b shows that 37% reported that PT was not feasible for their commute, whereas 59% reported that PT was available.

6.6. Behavioural mechanisms and synthesis

This chapter presents the empirical results and interprets the behavioural mechanisms underlying commuters' adaptation to planned roadworks. The purpose of this section is to integrate that evidence into a set of behavioural mechanisms that can be carried forward to the Chapter 7.

The synthesis follows the results. The SC models identify average trade-offs and structural constraints (benchmark MNL) and whether these trade-offs vary across individuals (MXL and LC). The pivot module identifies how adaptation changes with disruption severity when the scenario is anchored to the respondent's own commute. Finally, the RP module provides an empirical check on realised behaviour and on constraints that are difficult to capture with attribute-based stated-choice tasks. Together, these components provide evidence on the drivers of adaptation and its limits.

Beyond this internal triangulation, the combination of stated and revealed information is also relevant for interpreting external validity and hypothetical bias. Differences between stated and realised behaviour may arise when real-world uncertainty, imperfect information, and transaction costs become binding (Beck et al., 2016; Hensher, 2010). This is examined explicitly in Section 6.7.

6.6.1. Working from home as constraint-driven adaptation

A consistent finding across the SC, pivot, and RP components is that WFH behaves less like a marginal-mode substitute and more like an adaptation channel, enabled or blocked by job-related constraints.

In the SC benchmark MNL (Table 6.2), WFH utility is strongly influenced by on-site obligations and feasibility constraints. The on-site coefficients are large, negative, and ordered ($\beta_{\text{on-site, Medium}} = -1.63$; $\beta_{\text{on-site, High}} = -3.70$), and the feasibility indicator is positive and significant ($\delta_{\text{WFH, Feasible}} = 1.92$). This pattern indicates that the ability to choose WFH depends materially on whether the respondent can work from home and on the degree to which the job requires presence. Importantly, this is not a subtle second-order effect. The magnitude and precision of these parameters imply that job constraints are a first-order determinant of whether WFH is part of the effective choice set.

The baseline simulation (Figure 6.1) illustrates how these constraints translate into substitution patterns as the delay increases for a representative commuter profile. As the additional delay increases, the probability of choosing the car declines, while the likelihood of the non-car options increases. For the specific baseline profile assumed in the simulation, the model predicts that public transport becomes slightly more attractive than WFH. This illustrates that, even when WFH is feasible, on-site obligations can reduce its relative attractiveness compared with travel alternatives.

The determining role of constraints is further highlighted by the contrast between a flexible commuter (WFH feasible, low obligations) and a fixed commuter (WFH infeasible, high obligations) in Figure 6.2. The flexible profile exhibits a much earlier and steeper decline in car-choice probability, whereas the fixed profile retains a substantially higher probability of remaining in the car category across the delay range. This pattern supports the interpretation that observed car dependence is not solely a preference for driving, but can be structurally reinforced when the main non-travel substitute (WFH) is unavailable or unattractive.

Finally, Figure 6.3 contextualises the magnitude of employer-related constraints relative to delay sensitivity by comparing car choice under different levels of on-site obligations. The curves differ in baseline car dependence and in the rate of decline in car use with increasing delay, indicating that employer constraints shape the resilience of car commuting under disruption. Nevertheless, switching probabilities remain moderate, reflecting strong baseline resistance captured by the alternative-specific constants.

This interpretation aligns with prior evidence that WFH adoption is primarily shaped by job- and employer-related constraints. WFH becomes behaviourally relevant primarily when it is feasible within the job and supported by the organisation; when these conditions are not met, preferences or travel-time incentives alone are unlikely to translate into actual WFH behaviour (Peters et al., 2004). More generally, empirical studies consistently show that WFH uptake differs strongly across occupations and employer contexts, while travel conditions tend to play a secondary role once feasibility and organisational constraints are taken into account (Walls et al., 2007).

The pivot module refines this interpretation by identifying which specific constraints are most consequential under disruption. While the descriptive trends show increasing substitution to WFH at higher disruption levels (Table 6.7), the preferred pivot model indicates that tasks requiring physical presence substantially reduce WFH utility ($\beta_{\text{Location}} = -3.26$), while WFH feasibility increases the propensity to choose WFH ($\beta_{\text{WFH, Feasible}} = 2.26$; Table 6.8). Together, these results imply a hierarchy of constraints. Physical presence strongly limits WFH as an adaptation channel, while WFH feasibility is a prerequisite for WFH to become relevant once disruption becomes substantial.

Post-COVID evidence from the Netherlands similarly shows that homeworking became widespread, yet remains strongly uneven across occupations and organisational contexts, implying that a high system-level WFH majority does not eliminate binding constraints at the individual level (Centraal Bureau voor de Statistiek (CBS), 2024; de Haas et al., 2020). Taken together, the SC, pivot, and RP results support a single mechanism. WFH is an adaptation channel that becomes relevant under substantial disruption, but the extent of WFH adaptation is determined primarily by feasibility and on-site requirements rather than by marginal travel attributes alone.

6.6.2. Public transport switching primarily constrained by baseline barriers

A second stylised result is that public transport switching is constrained primarily by baseline resistance and/or feasibility barriers, rather than by marginal PT travel time within the experimental range.

In the SC benchmark MNL, the PT travel-time coefficient is not statistically significant ($p = 0.294$), whereas the PT constant is large and negative ($ASC_{\text{PT}} = -7.65$; Table 6.2). This combination implies that, for the average respondent in this (car-oriented) sample, PT uptake is not well explained by incremental changes in PT travel time alone. Instead, the large negative baseline component indicates persistent factors not captured by the limited attribute set.

This interpretation is consistent with review evidence that mode shift from car to PT is often limited by perceived and experienced quality barriers, which are only partially proxied by in-vehicle travel time (Redman et al., 2013). Behaviourally, such barriers are reinforced by habit and affective/identity-related correlates of car use. Evidence from the literature indicates strong associations between car use, habits, and attitudes that help explain persistence even when objective conditions deteriorate (Gardner & Abraham, 2008).

The MXL and LC results are consistent with this interpretation. Across the preferred MXL specification, PT time remains insignificant while the PT baseline is strongly negative (Table 6.4). In the preferred LC model, PT baseline resistance also remains substantial and is not the primary dimension along which classes are separated (Table 6.6), indicating that the most salient heterogeneity in this dataset lies elsewhere, rather than in PT-time valuation.

The pivot evidence adds a complementary nuance. Although baseline resistance is strong, PT becomes more relevant once disruption becomes substantial. In the pivot module, PT switching is close to zero at the low disruption level and only emerges once disruption becomes substantial (Table 6.7). This pattern aligns with the view that PT is not a near substitute that car commuters readily adopt in response to small changes, but rather a response that becomes relevant only when disruption is large enough to overcome baseline resistance. This is closely related to inertia-based discrete choice formulations, where a mode-specific stickiness term can dominate marginal attribute changes (Gao & Sun, 2018).

The RP results provide direct evidence that both structural and behavioural barriers matter. A non-trivial share of respondents who continued driving reported that PT was not feasible for their commute, while a larger share reported that PT was feasible yet still continued by car (Figure 6.9b). This indicates that limited PT switching is not solely due to feasibility. Inertia and switching frictions remain important even when PT is reported as available.

6.6.3. Time cost trade-offs and heterogeneity in time sensitivity

A third mechanism concerns how commuters value time losses and how strongly this valuation varies across the population. The SC benchmark MNL indicates that both car travel time and car cost enter the utility function negatively and with high precision (Table 6.2). This is the basic behavioural foundation of the disruption response. Roadworks-induced time losses impose disutility, and commuters can respond by substituting out of car commuting when alternative options are sufficiently attractive and feasible.

However, the MXL results show that the strength of time sensitivity differs meaningfully across individuals. In the MXL specification, the estimated standard deviation of car travel-time sensitivity is significant (Table 6.4), indicating that the population is not well represented by a single average time parameter. This is important for interpretation because the same level of disruption can generate very different behavioural responses among commuters.

The LC model translates this continuous heterogeneity into two interpretable segments (Table 6.6). In the preferred LC specification, Class 1 is more delay-sensitive (more negative $\beta_{\text{Time,Car}}$) but has a lower baseline propensity for WFH (more negative ASC_{WFH}), whereas Class 2 is more delay-tolerant and has a higher baseline propensity for WFH. Consistent with the simulation results, the predicted car-choice probability declines faster for Class 1 as delay increases, while Class 2 retains a higher probability of remaining in the car category across much of the delay range.

Importantly, the LC results indicate that differences in delay sensitivity interact with baseline propensities. In the preferred LC specification (Table 6.6), Class 1 is more delay-sensitive (more negative

$\beta_{\text{Time,Car}}$) but has a lower baseline propensity for WFH (more negative ASC_{WFH}), whereas Class 2 is more delay-tolerant and has a higher baseline propensity for WFH. In the simulation results (Figure 6.5), the predicted car-choice probability therefore declines faster for Class 1 as delay increases, while Class 2 remains more persistent across much of the delay range. The key implication is that heterogeneity is structured: the same increase in delay can trigger markedly different levels of car persistence across segments.

Finally, the LC membership model links these behavioural differences to observable characteristics (Table 6.6). Age and higher education increase the log-odds of membership in Class 2 (relative to Class 1). Consistent with Figure 6.6, this implies that aggregate delay sensitivity is not uniform across socio-demographic profiles and that differences in persistence arise through both class membership and class-specific sensitivities.

6.6.4. Threshold response to delay

The pivot component indicates a nonlinear disruption-response pattern and a tolerance band at low disruption levels.

Descriptively, choice shares exhibit a sharp drop in car persistence between the 25% and 45% scenarios (Table 6.7). At a 25% increase in delay, persistence in the car category is near-complete, and PT switching is effectively absent. Between 25% and 45%, car share declines sharply, and substitution toward WFH (and, to a lesser extent, PT) becomes substantial. This pattern is difficult to reconcile with a purely continuous-substitution story in which each extra minute smoothly shifts the probabilities.

Such non-linearity is consistent with bounded-rationality approaches that allow for indifference bands in which travellers do not respond to small-to-moderate changes and only switch once a threshold is exceeded (Di et al., 2017). In Dutch field contexts, evidence from peak-avoidance reward experiments similarly shows that behavioural change depends strongly on habit and work-schedule flexibility, suggesting that modest disturbances can leave routines largely intact until incentives become sufficiently strong (Ben-Elia & Ettema, 2011).

In the preferred specification, the tolerance parameter is positive and significant (Table 6.8), implying that the low-disruption scenario entails an additional utility component that keeps commuters in their routine beyond what would be predicted by time sensitivity alone. After that tolerance band is removed, the time-sensitivity term dominates, and the model reproduces the observed collapse in car share.

To move beyond aggregate shares, Figure 6.8 visualises switching probability as a function of absolute additional travel time for two segments. The pattern suggests earlier non-zero switching among flexible workers and a stronger increase at higher disruption levels among location-bound workers, with an indicative crossover at severe delay. This pattern is consistent with different constraint sets across segments. Flexibility may enable earlier adaptation, whereas on-site requirements may generate stronger inertia at modest delays, followed by a more abrupt change once the disruption becomes sufficiently burdensome. At the same time, the figure should be interpreted as descriptive evidence within the sample. It is based on a limited number of delay points and, by itself, does not identify the exact substitute chosen for each segment. The key implication is the nonlinearity of the response and its interaction with constraints, rather than the existence of precise population-wide cutoff values.

6.7. External validity: intention-behaviour gap

This section compares hypothetical adaptation in the Pivot module to reported behaviour in the Revealed Preference (RP) module. This is done to assess whether the magnitude of stated switching is consistent with reported real-world behaviour under disruption.

Comparison of Pivot predictions with RP car persistence

Figure 6.10 contrasts the Pivot model prediction with observed Pivot choice shares and the RP choice shares. Importantly, the RP question did not measure the duration or magnitude of the disruption in minutes; hence, the RP shares cannot be interpreted as conditional on a specific additional delay Δt. To enable a visual comparison, the RP shares are included as horizontal reference lines (and corresponding star markers) and are aligned to the average additional delay in the Pivot sample ($\approx$

19 minutes), purely as a plotting anchor. This visual alignment is illustrative only and should not be interpreted as validation at $\Delta t \approx 19$ minutes.

At $\Delta t \approx 19$ minutes, the Pivot model predicts a car share of approximately 43%, whereas the RP module reports that 74.5% of respondents remained in the car category during experienced disruption episodes. This difference indicates a sizeable intention–behaviour gap: respondents state more willingness to adapt in the Pivot scenarios than is reflected in reported past behaviour.

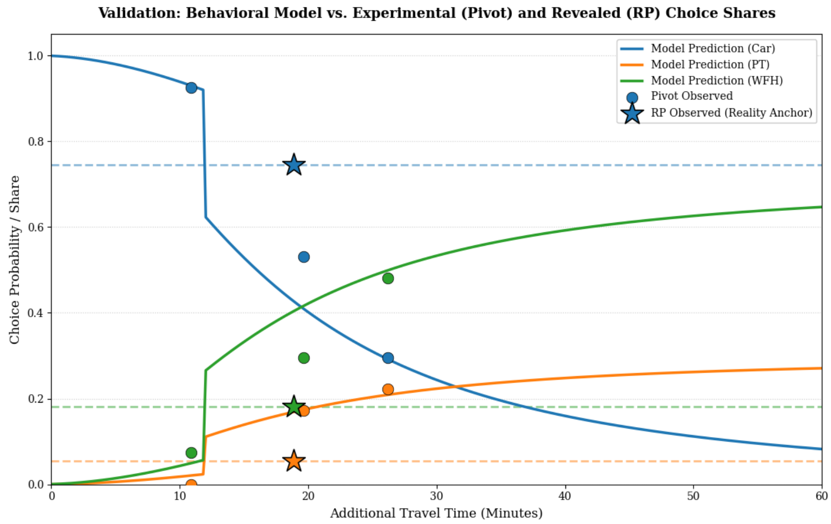


Figure 6.10: Pivot versus RP comparison. Solid lines show model-predicted choice shares as a function of additional travel time Δt; dots show observed Pivot shares at the three disruption levels; horizontal dashed lines (and star markers) indicate RP choice shares, which are unconditional on disruption duration and included as a reference anchor.

Interpretation and implications for external validity

The intention-behaviour gap should be interpreted cautiously because the Pivot and RP settings are not identical. In the Pivot module, the additional delay is presented ex ante, and respondents make their choices in a controlled setting that isolates adaptation options. In the RP module, disruption experiences are reported retrospectively and may involve uncertainty, imperfect information, and constraints that only become apparent during the trip. These contextual differences can increase real-world inertia relative to stated intentions. This also suggests that part of the observed intention–behaviour gap may be consistent with predictability and information effects discussed in the literature. In the Pivot module, respondents evaluate disruptions under clearly specified, ex-ante known conditions, whereas real-world roadworks may involve uncertainty about actual delays, durations, and the reliability of available information. The present study does not directly identify this mechanism, but the contrast between the stated and reported real-world settings is consistent with the hypothesis that lower predictability increases car persistence and dampens realised adaptation.

Nevertheless, the existence of such gaps is consistent with the hypothetical-bias and external-validity literature in transport, which documents that stated responses can deviate materially from revealed behaviour and discusses mechanisms such as lack of consequentiality, optimism about feasibility, and simplified decision processes in SP tasks (Beck et al., 2016; Hensher, 2010). In particular, certainty-calibration work shows that self-reported uncertainty is systematically related to divergence from revealed behaviour, implying that part of the gap can reflect overstatement of adaptation when respondents do not fully commit to the hypothetical choice (Beck et al., 2016).

The comparison remains informative for interpretation. The Pivot module captures the qualitative structure of the response (high persistence under low disruption and increased substitution under higher disruption), while the RP evidence suggests that the magnitude of inertia in real disruption contexts is substantial. In the conclusions chapter, this external validity insight is used to interpret the model outcomes conservatively with respect to realised switching rates, while retaining the behavioural mechanisms identified in the stated-choice components.

6.8. Comparison with the literature

The findings indicate that disruption severity reshapes commuter behaviour in a structured but non-linear way. Across the stated scenarios, small disruptions largely fall within a tolerance range in which the car category remains dominant, whereas stronger disruptions trigger a pronounced shift away from the car. In the pivot scenarios, this transition is reflected in a sharp reduction in car choice from 92.6% (low) to 53.1% (medium), and further to 29.6% (high), with the reduction primarily driven by working from home (WFH) and, secondarily, by public transport (PT). The interpretation is therefore not simply that greater delay causes more switching, but that commuters behave as if an indifference band applies at low disruption and re-optimise only once the increase in generalised burden becomes salient enough to justify switching costs. This aligns with threshold-based perspectives in travel choice modelling, where travellers may disregard small attribute differences and respond discretely once differences exceed a behavioural threshold (Obermeyer et al., 2015). It also accords with commuting time tolerance, in which modest increases are absorbed but stronger responses occur once a personal tolerance boundary is exceeded (He et al., 2016). In practice, this implies that representing roadwork impacts with a single smooth elasticity can misrepresent behaviour precisely in the severity range where adaptation accelerates.

A second central result is that WFH behaves less like a marginal mode and more like a constraint-gated adaptation channel. The estimated effects and scenario patterns point consistently to feasibility and on-site requirements as first-order determinants of whether WFH enters the effective choice set and can absorb disruption-induced substitution away from the car. This mechanism aligns with post-pandemic commute modelling that treats WFH as an explicit behavioural alternative whose uptake depends jointly on travel conditions and work context, and uses this structure for planning-relevant prediction (Hensher et al., 2024). It is also consistent with evidence that WFH does not merely replace the commute but reshapes broader activity-travel behaviour and scheduling, implying it should not be treated as a commute-only substitution mechanism (Rafiq et al., 2022).

The PT results provide a complementary picture. PT switching is present but bounded, and strongly conditioned by baseline resistance and the need for a sufficiently large push before commuters overcome inertia. This is consistent with the notion of path dependence in travel behaviour, where substantial shocks are often required for durable changes in public transport use, while smaller disruptions may leave habitual behaviour largely intact (Aarts et al., 1997; Cantillo et al., 2007; Fujii & Gärling, 2005; Ingvardson et al., 2025). Against this background, the modest PT uptake in the stated scenarios is not unexpected: even when disruption makes driving less attractive, PT must still compete with entrenched preferences, perceived inconvenience, and corridor-specific feasibility constraints. More generally, the determinants of commuting mode choice vary over time and across population segments, such that average responses can conceal meaningful heterogeneity in how alternatives are evaluated (Keyes & Crawford-Brown, 2018). In this thesis, heterogeneity manifests in varying sensitivities and baseline propensities to substitute, which help explain why increasing severity does not yield a uniform modal shift.

The combination of reduced car volumes and a strong WFH response also connects to the traffic evaporation discussion. When road capacity is reduced, or car travel becomes more burdensome, observed volumes can decline without one-to-one displacement to alternative routes, reflecting behavioural adjustments such as rescheduling, destination changes, or suppressed trips. Evidence from tactical urbanism interventions similarly suggests that capacity reductions can be accompanied by net traffic reductions rather than full diversion, highlighting behavioural adaptation beyond rerouting alone (Cairns et al., 2001; Nello-Deakin, 2022). While the institutional setting differs from planned roadworks, the conceptual implication carries over: under higher generalised costs, part of car travel demand may reallocate to non-travel responses (including WFH) and other adjustments, and it is preferable to model this explicitly rather than treat it as an unexplained residual.

A final interpretive point concerns external validity and the magnitude of predicted switching. The revealed-preference responses indicate substantially higher car persistence during experienced disruptions (74.5% reporting continued car use) than the stronger substitution observed in the stated-preference scenarios at comparable plotting anchors. This divergence is best interpreted as evidence that real-world behaviour may involve stronger inertia, uncertainty, and transaction costs than controlled hypothetical tasks capture, consistent with the stated-choice validity literature on hypothetical bias and external validity (Haghani et al., 2021). The most defensible use of the stated results is therefore structural: they establish direction, non-linearity, and the role of constraints in shaping, which substitutes for adaptation. Translating these findings into absolute switching magnitudes for a specific project context requires conservative interpretation and, ideally, calibration against revealed data with measured disruption severity.

7 Conclusion and discussion

In this final chapter, the results of the conducted study are summarised and discussed. First, a conclusion is presented that answers the research questions. Next, the study's limitations are outlined, and recommendations for Sweco and future research are provided.

7.1. Conclusion

The objective of this thesis was to understand how working commuters adapt to planned temporary roadworks in the Netherlands, with specific attention to how disruption severity reshapes the balance between continuing to drive, switching to public transport, and working from home. The main research question, therefore, examined how increasing disruption severity changes commuters' stated responses, and how these responses are mediated by work-related constraints and behavioural heterogeneity.

How does the severity of temporary roadworks disruptions shape working commuters' mode choice and WFH responses in the Netherlands?

To answer the main research question, the following sub-research questions were addressed. The next section answers each sub-question, followed by an integrated response to the main research question.

SQ1: What are the relevant effects of planned temporary roadworks on commuting behaviour?

Planned temporary roadworks primarily affect commuting by increasing the burden of the car commute, which activates a hierarchy of behavioural responses rather than a single adjustment. A common first line of adaptation discussed in the disruption literature is intramodal adjustment: commuters try to maintain car travel by rerouting and/or retiming as long as feasible detours remain available. Intermodal substitution, such as switching to public transport, and activity-based/non-travel responses (notably working from home) become salient mainly when disruption costs rise beyond what can be absorbed through tolerable within-mode adjustments. This ordering is not presented as universal; where detour possibilities are structurally poor, larger shifts and non-travel responses are more likely. Overall, planned roadworks can trigger intramodal adjustments, intermodal substitution, and activity-based adaptation, and explicitly recognising the non-travel pathway is important to avoid treating reduced car volumes as unexplained demand loss.

SQ2: Which factors are associated with working from home during planned roadworks disruptions?

Working from home during planned roadworks is primarily a constraint-enabled adaptation rather than a uniformly available substitute for commuting. The most decisive associations are structural: WFH uptake during disruption is strongly shaped by whether work can realistically be performed from home and by whether roles, tasks, or employer expectations require physical on-site presence. Where such presence obligations are binding, increased disruption does not readily translate into higher WFH; where they are not, WFH becomes a salient option as disruption becomes more substantial.

At the same time, feasibility does not fully determine behaviour. Among commuters for whom WFH is possible, there remains meaningful variation in baseline propensity to use WFH as an adaptation option. This implies that disruption activates WFH only for a subset of commuters and that, within the feasible group, responses still differ in how readily WFH is used as commuting becomes more burdensome.

SQ3: How does disruption severity affect the likelihood that car commuters switch to public transport or choose working from home?
Increasing disruption severity—captured as larger travel-time penalties—reduces persistence in car commuting and shifts behaviour toward two substitute responses: working from home (WFH) and, to a lesser extent, public transport (PT). This shift is not gradual across all severity levels. Instead, minor disruptions typically fall within a tolerance range in which most commuters remain in the car category, whereas more substantial disruptions trigger a markedly stronger reallocation away from the car.

This non-linearity is most clearly visible between low and moderate disruption: car share drops from roughly 93% to about 53%, while WFH rises to around 30% and PT to around 17%. At higher severity, WFH becomes the leading substitute when feasible, while PT can become increasingly relevant when disruption is substantial enough for some commuters to move beyond baseline resistance to switching.

Crucially, the severity effect is mediated by constraints. Where on-site presence requirements are binding, severity-induced adaptation cannot translate into WFH to the same extent and therefore tends to materialise more through PT (once disruption becomes sufficiently burdensome). Conversely, among commuters with greater flexibility, substitution starts earlier and is more likely to take the form of WFH rather than PT. In this way, severity governs the overall pressure to adapt, while feasibility and presence constraints largely determine which alternative absorbs the shift away from car use.

SQ4: Which factors explain differences in responses to planned roadworks disruptions?
Differences in how commuters respond to planned roadworks are explained by the interaction between constraints that shape the feasible choice set and genuine preference heterogeneity in the perception of disruption costs and the valuation of substitutes. As a result, identical increases in travel-time burden do not translate into uniform behavioural change across commuters.

First, constraints fundamentally alter the set of options. For some commuters, on-site requirements effectively preclude WFH as a realistic option, whereas for others, WFH is available but constrained by workplace expectations and fixed presence patterns. In parallel, switching to public transport is not equally viable across commuters, and for part of the sample, the relevant limitation is not only feasibility but also a baseline reluctance to switch modes.

Second, commuters differ in behavioural sensitivities and baseline propensities: some perceive delays as strongly disruptive and substitute earlier, whereas others exhibit greater inertia unless disruption becomes extreme. These differences help explain why severity produces different switching onset points and why the same disruption can lead to different compositions of adaptation across groups. Part of this heterogeneity aligns with observable characteristics such as age and education, suggesting that adaptation potential is more concentrated in specific subgroups rather than evenly distributed.

7.1.1. Integrated answer to the main research question

Overall, disruption severity, measured as increased time burden during the car commute, shifts commuters away from routine car use toward two substitutes: working from home and, to a lesser extent, public transport. This relationship is best understood as non-linear rather than as a single smooth elasticity: small disruptions often fall within a tolerance range in which the car category remains dominant, whereas more substantial disruptions trigger a sharper shift from absorbing delay to actively substituting away from car commuting.

Which substitute absorbs this shift is primarily determined by constraints and heterogeneity. When WFH is feasible and presence requirements are limited, disruption-induced adaptation is channelled primarily into WFH as a non-travel response. Where work is location-bound or on-site obligations bind, WFH is structurally lower, and substitution is more likely to materialise through PT if PT is a realistic alternative. At the same time, behavioural responses are unevenly distributed: differences in delay sensitivity and baseline propensity to use WFH imply that severity does not produce uniform changes across commuters.

Finally, the translation of stated responses into realised switching magnitudes should be treated cautiously. Self-reported behaviour during experienced disruptions indicates substantially higher persistence in the car category, and among those who do change behaviour, WFH is reported more often than switching to PT. The most defensible conclusions, therefore, concern the direction and structure of the response mechanism; precisely realised switching magnitudes depend on context and constraints, as elaborated in the limitations.

7.2. Limitations

This thesis has several limitations that are important for interpreting the strength, transferability, and practical use of the findings. Overall, the evidence is strongest regarding the direction and structure of the identified behavioural mechanisms, and more caution is warranted when translating stated responses into realised switching magnitudes under specific roadworks conditions.

Hypothetical severity evidence and external validity of magnitudes

A central limitation is that the core severity evidence is derived from stated-choice tasks that assume respondents can translate hypothetical, ex-ante known disruption conditions into credible behavioural choices. Real-world roadworks and disruptions can involve uncertainty, imperfect information, and transaction costs, all of which may increase inertia relative to stated intentions. The thesis itself documents a substantial intention–behaviour gap when comparing stated outcomes with self-reported realised behaviour during experienced disruptions. Consequently, the magnitude of the predicted switching away from the car at a given severity level should be treated conservatively, conditional on the survey framing, whereas the qualitative conclusions about how severity reshapes behaviour are more robust.

Relatedly, the revealed-preference module is informative for validating qualitative ordering, but it is not conditioned on a measured disruption magnitude and duration in comparable units. This limits severity-conditional validation and prevents the thesis from directly calibrating a specific pivot-implied elasticity to a specific realised delay level. A clear next step is to collect revealed-behaviour data that includes disruption magnitude and duration measures aligned to the stated severity framing, and to strengthen triangulation with additional behavioural traces where feasible.

Beyond these external validity considerations, transferability of the aggregate magnitudes is also constrained by the composition of the analytical sample.

Sample composition and transferability

The analytical survey sample is modest and explicitly not presented as population-representative. Benchmarking indicates a skew toward younger, higher-educated respondents relative to the reference populations, and parts of the empirical analysis are restricted to a car-commuter subsample. This matters because several mechanisms central to the thesis, particularly workplace flexibility, WFH feasibility, and heterogeneity linked to socio-demographics, are unevenly distributed across the broader commuting population. As a result, conclusions about the prevalence of work-constraint profiles and the implied aggregate switching potential may not transfer one-to-one to the Dutch commuter population at large, even if within-sample behavioural patterns remain interpretable. More specifically, because the analytical sample is skewed toward younger and higher-educated respondents, and because the stated-choice setting presents WFH as an available response under clearly specified disruption conditions, the estimated scope for WFH-based adaptation may be somewhat overstated relative to the wider commuter population or to realised behaviour under real-world frictions. This directional caveat should, however, be interpreted cautiously, as the thesis does not identify the exact magnitude of such bias. In addition, the pivot and revealed-preference evidence are conditional on the car-commuter subsample, which further constrains the transferability of any segment composition or threshold interpretation beyond the observed sample. A direct extension is to recruit a larger, more diverse commuter sample to test whether the same mechanisms persist and how segment prevalence shifts under more representative distributions of job types and flexibility.

Restricted choice set and omitted adaptation channels

The empirical choice set is deliberately restricted to three alternatives. Many real-world adaptations, such as rerouting, retiming, trip chaining, destination substitution, or switching to other modes, are therefore not modelled as explicit alternatives. This design choice is consistent with the thesis's focus on substituting away from the car toward PT or non-travel, but it has two important implications. First, observed car persistence should be interpreted as persistence within the restricted substitution set; in practice, this may include substantial within-car adjustments that are not separately identified. Second, the study cannot provide a complete behavioural accounting of how the full bundle of adaptations reallocates across channels as severity rises. Future work could address this by extending the stated-choice design to explicitly represent key intramodal options or by adopting a two-stage framing in which within-mode adjustments are elicited before intermodal or non-travel choices, allowing severity to be mapped more transparently onto the full hierarchy of responses.

Measurement and simplification of constraints and public transport barriers

Several key explanatory constructs, such as WFH feasibility, on-site obligations, and location dependence, are operationalised through self-reported indicators and necessarily simplified scenario descriptions. While these measures are substantively meaningful and consistently shape behaviour in the results, they compress substantial task-level and organisational nuance into parsimonious categories. Measurement error or misclassification can therefore affect the estimated strength and ordering of constraint mediation, particularly near the lower end of the severity scale, where behavioural differences are subtle.

In addition, the public transport alternative is represented in a generic manner using a limited set of attributes. This supports the thesis's conclusion that PT uptake is bounded by baseline barriers and not driven strongly by marginal changes in PT travel time in the stated setting, but it does not identify which specific PT barriers (beyond travel time) dominate in this dataset. Accordingly, the thesis is better suited to concluding that PT resistance exists and matters than to deriving targeted, attribute-specific PT intervention priorities.

7.3. Recommendations for Sweco

The recommendations below are directed at applied planning and modelling practice at Sweco. They translate the core behavioural mechanisms identified in this thesis, a non-linear severity response, constraint-gated substitution (especially for WFH), bounded PT switching, and an intention–behaviour gap, into practical guidance for scenario design, appraisal, and communication. Appendix K complements these recommendations by providing a concise, practical translation of the main findings for project work, client conversations, and scenario construction. The aim is therefore not to replace one simplified assumption with another default percentage, but to support a more transparent and empirically grounded approach to selecting, interpreting, and communicating behavioural assumptions. First, scenario design should distinguish at least between low-disruption and moderate-to-high-disruption regimes, rather than applying a uniform reduction factor across all severities. In practice, Sweco can operationalise this by defining a small number of severity tiers and reporting outcomes per tier as ranges rather than point estimates. Each project should explicitly document the assumed tier, explain why that tier is plausible given the project context, and quantify the sensitivity of the results to moving up or down by one tier.

Second, WFH should be explicitly represented as a constraint-driven adaptation channel in peak-period demand assessments, rather than being absorbed into an undefined, disappearing traffic term. The evidence in this thesis indicates that WFH uptake under disruption is primarily gated by feasibility and on-site presence requirements, and therefore cannot be assumed to apply uniformly across commuters. A practical implementation step is to represent demand using at least two broad groups with distinct feasible option sets, such as higher versus lower WFH feasibility / on-site obligations, and to carry these groups through scenario appraisal and stakeholder communication. In practice, this should not be read as requiring precise identification of individual commuters, which is often infeasible in project settings. Rather, the segmentation can be approximated using available contextual information, such as corridor type, trip purpose, employment structure, stakeholder input, or simple scenario assumptions about the share of commuters with greater versus lower flexibility. This enables reporting on where demand reduction is plausibly driven by WFH and where other measures may be more relevant, while remaining transparent about the uncertainty in the segment assumptions.

Third, planning assumptions should not treat PT as an automatic substitute for marginal changes in relative travel time. Within the scope of this study, PT switching appears to be bounded by baseline resistance and feasibility constraints, and to become behaviourally relevant mainly under more substantial disruption or when other substitutes (notably WFH) are constrained. For project practice, this implies that PT-related mitigation packages should be interpreted in a barrier-oriented way: if PT uptake is an objective, the focus should be on diagnosing and addressing the binding barriers in the corridor context, rather than assuming that modest relative travel-time improvements will yield large shifts.

Finally, when using these findings for ex-ante appraisal or forecasting, Sweco should translate stated responses into conservative ranges rather than point estimates. The thesis indicates that realised behaviour can exhibit stronger inertia than stated scenarios imply, and that revealed evidence in this study does not condition directly on comparable severity magnitudes. A practical step is to report scenario outcomes as bounded intervals and to separate conclusions that are robust to external validity uncertainty from those that are not. Where feasible, projects should include simple validation checks using available operational data to ensure that assumed behavioural responses remain plausible in the applied context .

7.4. Recommendations for future research

The recommendations below indicate how future research can strengthen the evidence base for predicting and managing commuter responses to planned roadworks, building directly on the limitations and empirical insights of this thesis.

First, future studies should collect revealed-behaviour data that measure disruption severity across comparable units. This would enable severity-conditional validation of stated-choice findings and improve the calibration of switching magnitudes under real-world conditions.

Second, future stated-choice designs could include explicit intramodal alternatives, such as rerouting and retiming, or adopt a two-stage framework in which within-mode adjustments are elicited before intermodal or non-travel choices. This would help disentangle ”car persistence” into unchanged versus adapted car travel and provide a more complete accounting of response pathways under roadworks.

Third, given that PT is represented generically in this thesis, future work should include additional PT-related attributes and more detailed feasibility measures to identify which barriers most strongly limit PT uptake under disruption. This would support more targeted intervention design and improve predictive realism for PT switching.

Fourth, future research should replicate the analysis with larger, more diverse commuter samples to assess how segment prevalence and aggregate response magnitudes vary under more representative distributions of age, education, job types, and workplace flexibility. This would strengthen transferability beyond the sample composition in this study.

Finally, because stated-choice tasks typically assume advanced knowledge of disruption conditions, future studies could test how responses change under more realistic information conditions, such as uncertainty about delay or duration, or variation in information quality. This would also help test whether part of the intention–behaviour gap observed in this thesis is driven by predictability and information effects rather than by severity alone.

Bibliography

Aarts, H., Verplanken, B., & Van Knippenberg, A. (1997). Habit and information use in travel mode choices. *Acta Psychologica*, *96*(1-2), 1–14. https://doi.org/10.1016/S0001-6918(97)00008-5

Adobati, F., & Debernardi, A. (2022). The breath of the metropolis: Smart working and new urban geographies. *Sustainability*, *14*(2), 1028. https://doi.org/10.3390/su14021028

Albert, G., & Mahalel, D. (2006). Congestion tolls and parking fees: A comparison of the potential effect on travel behavior. *Transport Policy*, *13*(6), 496–502. https://doi.org/10.1016/j.tranpol.2006.05.007

ANWB. (2024). 8 procent meer files op de nederlandse wegen in 2024. *ANWB*. https://www.anwb.nl/verkeer/nieuws/nederland/2024/december/filezwaarte-2024

ANWB-verkeersinformatie. (2025). Filezwaarte in september fors toegenomen. https://www.anwb.nl/verkeer/nederland/verkeersinformatie/filezwaarte

Ashour, L., & Shen, Q. (2025). Unveiling post-pandemic commute choices amidst the rise of telework. *Transportation Research Part D: Transport and Environment*, *149*, 105068. https://doi.org/10.1016/j.trd.2025.105068

Athanasiadou, C., & Theriou, G. (2021). Telework: Systematic literature review and future research agenda. *Heliyon*. https://www.cell.com/action/showPdf?pii=S2405-8440%2821%2902268-4

Avineri, E., & Prashker, J. N. (2006). The Impact of Travel Time Information on Travelers' Learning under Uncertainty. *Transportation*, *33*(4), 393–408. https://doi.org/10.1007/s11116-005-5710-y

Bamberg, S., Ajzen, I., & Schmidt, P. (2003). Choice of Travel Mode in the Theory of Planned Behavior: The Roles of Past Behavior, Habit, and Reasoned Action [Publisher: Routledge _eprint: https://doi.org/10.1207/S15324834BASP2503_01]. *Basic and Applied Social Psychology*, *25*(3), 175–187. https://doi.org/10.1207/S15324834BASP2503_01

Beck, M. J., Fifer, S., & Rose, J. M. (2016). Can you ever be certain? reducing hypothetical bias in stated choice experiments via respondent reported choice certainty. *Transportation Research Part B: Methodological*, *89*, 149–167. https://doi.org/10.1016/j.trb.2016.04.004

Ben-Elia, E., Bierlaire, M., & Ettema, D. (2010). A model of departure time choice with latent classes and peak-hour avoidance rewarding. Retrieved November 4, 2025, from https://uwe-repository.worktribe.com/index.php/output/977251/a-model-of-departure-time-choice-with-latent-classes-and-peak-hour-avoidance-rewarding

Ben-Elia, E., & Ettema, D. (2011). Rewarding rush-hour avoidance: A study of commuters' travel behavior. *Transportation Research Part A: Policy and Practice*, *45*(7), 567–582. https://doi.org/10.1016/j.tra.2011.03.003

Ben-Elia, E., Ettema, D., & Boeije, H. (2011). Behaviour change dynamics in response to rewarding rush-hour avoidance: A qualitative research approach. Retrieved November 4, 2025, from https://uwe-repository.worktribe.com/index.php/output/966874/behaviour-change-dynamics-in-response-to-rewarding-rush-hour-avoidance-a-qualitative-research-approach

Brown, A. E., Taylor, B. D., & Wachs, M. (2017). The Boy Who Cried Wolf? Media Messaging and Traveler Responses to "Carmageddon" in Los Angeles. *Public Works Management & Policy*, *22*(3), 275–293. https://doi.org/10.1177/1087724X16643544

Bueno, P. C., Gomez, J., Peters, J. R., & Vassallo, J. M. (2017). Understanding the effects of transit benefits on employees' travel behavior: Evidence from the New York-New Jersey region. *Transportation Research Part A Policy and Practice*, *99*, 1–13. https://doi.org/10.1016/j.tra.2017.02.009

Cairns, S., Atkins, S., & Goodwin, P. (2001). Disappearing traffic? The story so far.

Calvert, T., & Melia, S. (2023). Does traffic really disappear when roads are closed? *Proceedings of the Institution of Civil Engineers - Municipal Engineer*, *176*(1), 1–9. https://doi.org/10.1680/jmuen.21.00014

Cantillo, V., De Dios Ortúzar, J., & Williams, H. C. W. L. (2007). Modeling discrete choices in the presence of inertia and serial correlation. *www-jstor-org.tudelft.idm.oclc.org*. https://www-jstor-org.tudelft.idm.oclc.org/stable/25769346

Caussade, S., De Dios Ortúzar, J., Rizzi, L. I., & Hensher, D. A. (2004). Assessing the influence of design dimensions on stated choice experiment estimates. *Transportation Research Part B Methodological*, *39*(7), 621–640. https://doi.org/10.1016/j.trb.2004.07.006

CBS, C. B. S. (2024). Over half of dutch people work from home sometimes. *CBS*. https://www.cbs.nl/en-gb/news/2024/11/over-half-of-dutch-people-work-from-home-sometimes

Centraal Bureau voor de Statistiek. (2024a). *Bijna 11,7 miljoen mensen hebben autorijbewijs*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/nieuws/2024/08/bijna-11-7-miljoen-mensen-hebben-autorijbewijs

Centraal Bureau voor de Statistiek. (2024b). *Hoeveel LGBTQIA-personen telt nederland? – resultaten*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/longread/statistische-trends/2024/hoeveel-lhbtqia-personen-telt-nederland-/3-resultaten

Centraal Bureau voor de Statistiek. (2024c). *Mannen en vrouwen (dashboard bevolking)*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/visualisaties/dashboard-bevolking/mannen-en-vrouwen

Centraal Bureau voor de Statistiek. (2024d). *Onderweg in nederland (odin) 2023 – bijlage d: Kerntabellen*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/longread/rapportages/2024/onderweg-in-nederland--odin---2023-onderzoeksbeschrijving/bijlage-d-kerntabellen

Centraal Bureau voor de Statistiek. (2024e). *Onderweg in nederland (odin) 2023 – onderzoeksbeschrijving*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/longread/rapportages/2024/onderweg-in-nederland--odin---2023-onderzoeksbeschrijving

Centraal Bureau voor de Statistiek. (2024f). *Onderweg in nederland (odin) 2023 – plausibiliteitsrapportage*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/longread/rapportages/2024/onderweg-in-nederland--odin---2023-plausibiliteitsrapportage

Centraal Bureau voor de Statistiek. (2024g). *Rijbewijzen (verkeer en vervoer – visualisaties)*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/visualisaties/verkeer-en-vervoer/verkeer/rijbewijzen

Centraal Bureau voor de Statistiek. (2024h). *Werkzame beroepsbevolking; arbeidsduur (enquête beroepsbevolking)*. Retrieved January 29, 2026, from https://www.cbs.nl/nl-nl/cijfers/detail/85275NED

Centraal Bureau voor de Statistiek. (2024i). Thuiswerkers wonen kwartier verder van werk. https://www.cbs.nl/nl-nl/nieuws/2024/16/thuiswerkers-wonen-kwartier-verder-van-werk

Centraal Bureau voor de Statistiek (CBS). (2024). *Ruim helft nederlanders werkt weleens thuis*. Retrieved February 11, 2026, from https://www.cbs.nl/nl-nl/nieuws/2024/11/ruim-helft-nederlanders-werkt-weleens-thuis

Chalabi, G., & Dia, H. (2024). Telecommuting and travel behaviour: A survey of white-collar employees in adelaide, australia. *Sustainability*, *16*(7), 2871. https://doi.org/10.3390/su16072871

CROW, F. (1998). Reistijdvergelijking auto-OV en fiets - fietsberaad. https://www.fietsberaad.nl/kennisbank/reistijdvergelijking-auto-ov-en-fiets

Danczyk, A., Di, X., Liu, H. X., & Levinson, D. M. (2017). Unexpected versus expected network disruption: Effects on travel behavior. *Transport Policy*, *57*, 68–78. https://doi.org/10.1016/j.tranpol.2017.02.002

de Bekker-Grob, E. W., Donkers, B., Jonker, M. F., & Stolk, E. A. (2015). Sample size requirements for discrete-choice experiments in healthcare: A practical guide. *The Patient*, *8*(5), 373–384. https://doi.org/10.1007/s40271-015-0118-z

de Clercq, K. (2025, September). Interview on planned roadworks, commuter adaptation, and modelling practice at sweco [Personal interview, Sweco, September 2025].

De Graaff, T. (2004). On the substitution and complementarity between telework and travel: A review and application. https://research.vu.nl/ws/portalfiles/portal/2011594/20040016.pdf

de Haas, M., Faber, R., & Hamersma, M. (2020). How covid-19 and the dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the netherlands. *Transportation Research Interdisciplinary Perspectives*, *6*, 100150. https://doi.org/10.1016/j.trip.2020.100150

Desai, J., Scholer, B., Mathew, J. K., Li, H., & Bullock, D. M. (2022). Analysis of Route Choice During Planned and Unplanned Road Closures. *IEEE Open Journal of Intelligent Transportation Systems*, *3*, 489–502. https://doi.org/10.1109/OJITS.2022.3183928

Di, X., Liu, H. X., Zhu, S., & Levinson, D. M. (2017). Indifference bands for boundedly rational route switching. *Transportation*, *44*(5), 1169–1194. https://doi.org/10.1007/s11116-016-9699-1

EPOMM. (2011). Mobility budget: A new financial incentive for sustainable travel. https://epomm.eu/sites/default/files/eupdates/1203_en.pdf

Fearnley. (2016). Triggers of urban passenger mode shift - state of the art and model evidence. *AET*. https://aetransport.org/public/downloads/y9sOi/4792-57ce9b83ea601.pdf

Fujii, S., & Gärling, T. (2005). Temporary structural change: a strategy to break car-use habit and promote public transport. https://api.semanticscholar.org/CorpusID:10735248

Fujii, S., & Gärling, T. (2003). Development of script-based travel mode choice after forced change. *Transportation Research Part F: Traffic Psychology and Behaviour*, *6*(2), 117–124. https://doi.org/10.1016/S1369-8478(03)00019-6

Gao, K., & Sun, L. (2018). Incorporating inertia in mode choice and influential factors of car stickiness: Implications for shifts to public transit. *Promet – Traffic&Transportation*, *30*(3), 293–303. https://doi.org/10.7307/ptt.v30i3.2507

Gardner, B., & Abraham, C. (2008). Psychological correlates of car use: A meta-analysis. *Transportation Research Part F: Traffic Psychology and Behaviour*, *11*(4), 300–311. https://doi.org/10.1016/j.trf.2008.01.004

Guiver, J. (2011). TRAVEL ADJUSTMENTS AFTER ROAD CLOSURE: WORKINGTON.

Haghani, M., Bliemer, M. C. J., Rose, J. M., Oppewal, H., & Lancsar, E. (2021). Hypothetical bias in stated choice experiments: Part II. conceptualisation of external validity, sources and explanations of bias and effectiveness of mitigation methods. *Journal of Choice Modelling*, *41*, 100322. https://doi.org/10.1016/j.jocm.2021.100322

He, M., Zhao, S., & He, M. (2016). Tolerance threshold of commuting time: Evidence from kunming, china. *Journal of Transport Geography*, *57*, 1–7. https://doi.org/10.1016/j.jtrangeo.2016.09.007

Heinen, E., Maat, K., & Van Wee, B. (2012). The effect of work-related factors on the bicycle commute mode choice in the netherlands. *Transportation*, *40*(1), 23–43. https://doi.org/10.1007/s11116-012-9399-4

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B: Methodological*, *44*(6), 735–752. https://doi.org/10.1016/j.trb.2009.12.012

Hensher, D. A., Balbontin, C., Beck, M. J., & Wei, E. (2024). Commuting mode choice and work from home in the later stages of COVID-19: Consolidating a future focussed prediction tool to inform transport and land use planning. *Transportation Research Part A: Policy and Practice*, *187*, 104194. https://doi.org/10.1016/j.tra.2024.104194

Hensher, D. A., Rose, J. M., & Greene, W. H. (2005). Applied Choice Analysis. *Cambridge University Press*. https://doi.org/10.1007/9781316136232

Hess, S., Bierlaire, M., & Polak, J. W. (2005). Estimation of value of travel time savings using mixed logit models. *Transportation Research Part A: Policy and Practice*, *39*(2-3), 221–236. https://doi.org/10.1016/j.tra.2004.09.007

Hunt, J. D., Brownlee, A. T., & Stefan, K. J. (2002). Responses to Centre Street Bridge Closure: Where the “Disappearing” Travelers Went [Publisher: SAGE Publications Inc]. *Transportation Research Record*, *1807*(1), 51–58. https://doi.org/10.3141/1807-07

Ingvardson, J. B., Raveau, S., & Soza-Parra, J. A. (2025). Inertia and shock effects in public transport: The case of metro line 6 in santiago using smart card data. *Transportation Research Part A: Policy and Practice*, *192*, 104352. https://doi.org/10.1016/j.tra.2024.104352

Kemmerer, P., Brach, B., Kubiak, T., Singer, S., & Gianicolo, E. A. L. (2023). Association of risk perception and transport mode choice during the temporary closure of a major inner-city road bridge: Results of a cross-sectional study. *European Transport Research Review*, *15*(1), 34. https://doi.org/10.1186/s12544-023-00608-y

Kennisinstituut voor Mobiliteitsbeleid (KiM). (2022). *Kennisinstituut Voor Mobiliteitsbeleid*. https://www.kimnet.nl/documenten/2022/02/22/het-wijdverbreide-autobezit-in-nederland

Kennisinstituut voor Mobiliteitsbeleid (KiM). (2024). *Kerncijfers mobiliteit 2024*. Retrieved January 29, 2026, from https://www.kimnet.nl/documenten/2024/11/18/kerncijfers-mobiliteit-2024

Keyes, A. K. M., & Crawford-Brown, D. (2018). The changing influences on commuting mode choice in urban england under Peak Car: A discrete choice modelling approach. *Transportation Research Part F: Traffic Psychology and Behaviour*, *58*, 167–176. https://doi.org/10.1016/j.trf.2018.06.010

Meinherz, F. (2020). The dynamics of modal shifts in (sub)urban commuting: An empirical analysis based on practice theories. *ideas.repec.org*. https://ideas.repec.org/a/eee/jotrge/v86y2020ics0966692319310890.html

METRICS, C. (2025, July). *Ngene User Manual* (tech. rep.). https://files.choice-metrics.com/NgeneManual.pdf

Ministerie van Infrastructuur en Waterstaat. (2025a). Groot onderhoud wegen en vaarwegen. https://www.rijkswaterstaat.nl/over-ons/onze-organisatie/groot-onderhoud

Ministerie van Infrastructuur en Waterstaat. (2025b). A4: groot onderhoud De Hoek - Burgerveen. https://www.rijkswaterstaat.nl/wegen/projectenoverzicht/a4-groot-onderhoud-de-hoek-burgerveen

Nello-Deakin, S. (2022). Exploring traffic evaporation: Findings from tactical urbanism interventions in barcelona. *Case Studies on Transport Policy*, *10*(4), 2430–2442. https://doi.org/10.1016/j.cstp.2022.11.003

Noord-Holland. (2025). Verkeershinder: Vanaf 11 juli nieuwe wegwerkzaamheden a4 en... https://www.noord-holland.nl/Actueel/Archief/2025/Juli_2025/Verkeershinder_Vanaf_11_juli_nieuwe_wegwerkzaamheden_A4_en_A10

Oakil, A. T. M., Ettema, D., Arentze, T., & Timmermans, H. (2014). Bicycle commuting in the netherlands: An analysis of modal shift and its dependence on life cycle and mobility events. *International Journal of Sustainable Transportation*, *10*(4), 376–384. https://doi.org/10.1080/15568318.2014.905665

Obermeyer, A., Treiber, M., & Evangelinos, C. (2015). On the identification of thresholds in travel choice modelling. *Journal of Choice Modelling*, *17*, 1–9. https://doi.org/10.1016/j.jocm.2015.12.001

Parkes, S. D., Jopson, A., & Marsden, G. (2016). Understanding travel behaviour change during mega-events: Lessons from the London 2012 Games. *Transportation Research Part A: Policy and Practice*, *92*, 104–119. https://doi.org/10.1016/j.tra.2016.07.006

Peters, C. P., Tijdens, K. G., & Wetzels, C. (2004). Employees' opportunities, preferences, and practices in telecommuting adoption. *Information & Management*, *41*(4), 469–482. https://www-sciencedirect-com.tudelft.idm.oclc.org/science/article/pii/S0378720603000855#aep-section-id44

Rafiq, R., McNally, M. G., Uddin, Y. S., & Ahmed, T. (2022). Impact of working from home on activity-travel behavior during the COVID-19 pandemic: An aggregate structural analysis. *Transportation Research Part A: Policy and Practice*. https://doi.org/10.1016/j.tra.2022.03.003

Rahman, M. (2023). Commute mode switch and its relationship to life events, built-environment, and attitude change. *Transportation Research Part D: Transport and Environment*, *120*, 103777. https://doi.org/10.1016/j.trd.2023.103777

Redman, L., Friman, M., Gärling, T., & Hartig, T. (2013). Quality attributes of public transport that attract car users: A research review. *Transport Policy*, *25*, 119–127. https://doi.org/10.1016/j.tranpol.2012.11.005

Rose, J. M., & Bliemer, M. C. J. (2009). Constructing efficient stated choice experimental designs. *Transport Reviews*, *29*(5), 587–617. https://doi.org/10.1080/01441640902827623

Shires, J., Marsden, G., Docherty, I., & Anable, J. (2016). Forth Road Bridge Closure Survey: Analysis of Commuter Behaviour.

Shoup, D. C. (1997). Evaluating the effects of cashing out employer-paid parking: Eight case studies. *Transport Policy*, *4*(4), 201–216. https://doi.org/10.1016/s0967-070x(97)00019-x

Small, K. A. (2012). Valuation of travel time. *Economics of Transportation*, *1*(1-2), 2–14. https://doi.org/10.1016/j.ecotra.2012.09.002

Snyder, H. (2019). Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, *104*, 333–339. https://doi.org/10.1016/j.jbusres.2019.07.039

Thompson, R. J., Payne, S. C., Alexander, A. L., Gaskins, V. A., & Henning, J. B. (2021). A Taxonomy of Employee Motives for Telework. *Occupational Health Science*, *6*(2), 149–178. https://doi.org/10.1007/s41542-021-00094-5

Timmins, C., & Murdock, J. (2007). A revealed preference approach to the measurement of congestion in travel cost models. *Journal of Environmental Economics and Management*, *53*(2), 230–249. https://doi.org/10.1016/j.jeem.2006.08.002

Train, K. (2008). Estimation on stated-preference experiments constructed from revealed-preference choices. *ideas.repec.org*. https://ideas.repec.org/a/eee/transb/v42y2008i3p191-203.html

Tympakianaki, A., Koutsopoulos, H. N., Jenelius, E., & Cebecauer, M. (2018). Impact analysis of transport network disruptions using multimodal data: A case study for tunnel closures in Stockholm. *Case Studies on Transport Policy*, *6*(2), 179–189. https://doi.org/10.1016/j.cstp.2018.05.003

van Dijk, R. (2022). *The causation of disappearing traffic in the context of the Netherlands* [Master's thesis]. Retrieved September 15, 2025, from https://studenttheses.uu.nl/bitstream/handle/20.500.12932/43115/The%20causation%20of%20disappearing%20traffic%20in%20the%20context%20of%20the%20Netherlands.pdf?sequence=1&isAllowed=y

Walls, M., Safirova, E., & Jiang, Y. (2007). What drives telecommuting? the relative impact of worker demographics, employer characteristics, and job types. *Transportation Research Record: Journal of the Transportation Research Board*, *2010*(1), 111–120. https://doi.org/10.3141/2010-13

Warnaar, M., Wieman, G., & Lamers, S. (2024). Betaalbaarheid mobiliteitskosten 2024. https://mobiliteitsalliantie.nl/wp-content/uploads/2024/10/Nibud-Mobiliteitsonderzoek-2024-def.pdf#page=16.12

Weng, W., Morrison, M., Boyle, K., & Boxall, P. (2017). The effect of the number of alternatives in a choice experiment with an application to the Macquarie Marshes, AU. *AgEcon Search (University of Minnesota, USA)*. https://doi.org/10.22004/ag.econ.252836

Yang, L., Hipp, J. A., Adlakha, D., Marx, C. M., Tabak, R. G., & Brownson, R. C. (2015). Choice of commuting mode among employees: Do home neighborhood environment, worksite neighborhood environment, and worksite policy and supports matter? *Journal of Transport & Health*, *2*(2), 212–218. https://doi.org/10.1016/j.jth.2015.02.003

Ye, L., Mokhtarian, P. L., & Circella, G. (2012). Commuter impacts and behavior changes during a temporary freeway closure: The 'Fix I-5' project in Sacramento, California. *Transportation Planning and Technology*, *35*(3), 341–371. https://doi.org/10.1080/03081060.2012.673270

Yun, M., Herick, D., & Mokhtarian, P. (2011). Nonwork Travel Behavior Changes During Temporary Freeway Closure: The Fix I-5 Project in Sacramento, California. *Transportation Research Record: Journal of the Transportation Research Board*, *2231*, 1–9. https://doi.org/10.3141/2231-01

Zhang, H. M., Chen, Y.-R., Lim, R., & Qian, Z. (2012). What happens when a major freeway is closed for repair? *Transportation Research Record Journal of the Transportation Research Board*, *2278*(1), 134–144. https://doi.org/10.3141/2278-15

Zhu, S., & Levinson, D. (2008). A review of research on planned and unplanned disruptions to transportation networks. https://trid.trb.org/View/1410266

Zhu, S., Levinson, D., Liu, H. X., & Harder, K. (2010). The traffic and behavioral effects of the I-35W Mississippi River bridge collapse. *Transportation Research Part A: Policy and Practice*, *44*(10), 771–784. https://doi.org/10.1016/j.tra.2010.07.001

A

Scientific paper

Impact of roadworks severity on commuters' mode choice and working from home

Splinter Groenink
MSc Transport, Infrastructure and Logistics
Delft University of Technology
Delft, The Netherlands

***Abstract*—Temporary roadworks increasingly disrupt commuting in the Netherlands, yet behavioural adaptation is still weakly represented in roadworks appraisal. This paper examines how disruption severity reshapes commuter responses, with particular attention to continued car use, public transport (PT) switching, and working from home (WFH). The analysis is based on an online survey among working commuters and combines an attribute-based stated-choice experiment, a commute-time-pivoted stated-choice experiment, and a revealed-preference module on experienced major disruption ($N = 180$). The results show that adaptation to roadworks severity is non-linear: modest increases in car travel time are often tolerated, whereas stronger disruption triggers substantially more substitution away from routine car commuting. WFH emerges as the dominant substitute when feasible, while PT plays a secondary but meaningful role. Work-related constraints, especially WFH feasibility and on-site obligations, strongly condition the adaptation channel. Revealed responses indicate stronger car persistence than stated scenarios suggest, pointing to an intention–behaviour gap. The findings imply that roadworks demand reduction should not be treated as a uniform residual effect, but as the outcome of multiple behavioural response channels.**

***Index Terms*—temporary roadworks, disruption severity, commuter adaptation, mode choice, working from home, behavioural heterogeneity, stated-choice experiment**

I. Introduction

Temporary roadworks are becoming a more consequential source of commuter disruption in the Netherlands. Ageing transport infrastructure requires large-scale renewal and maintenance interventions, while congestion levels have again intensified in recent years, including outside the traditional peak periods [1]–[3]. As a result, commuters are increasingly confronted with periods when their usual travel patterns are disrupted not by incidental delays but by planned, and sometimes substantial, reductions in network performance over multiple days or weeks. Such interventions not only affect travel times and route conditions; they may also alter the viability of habitual travel choices and force commuters to reconsider whether to continue travelling by car, switch to another mode, or avoid the trip altogether. For transport planners and road authorities, the resulting challenge is therefore not limited to estimating detours or queue growth. Planned disruption also raises a behavioural question: under what conditions do commuters continue their routine car commute, and when do they adapt by switching to another mode or not travelling at all?

Previous research shows that travellers respond to temporary network disruption through a range of coping strategies rather than through a single adjustment. Empirical studies of planned and unplanned road closures show that commuters often first attempt to maintain their trip through intramodal responses such as rerouting or retiming, while stronger disruption can also induce intermodal switching or trip suppression [4]–[7]. These behavioural responses are important because they shape both the direct impact of disruption and the extent to which traffic is redistributed, reduced, or absorbed elsewhere. In this context, the idea of disappearing traffic, or traffic evaporation, captures an important network-level observation: traffic volumes under capacity constraints are not fully displaced to other routes because some travellers adapt their behaviour more fundamentally [8], [9]. However, disappearing traffic is an aggregate outcome rather than a behavioural mechanism in itself. To properly understand the impacts of roadworks, the underlying adaptation channels must be explicitly identified.

An important gap remains in how these channels are represented, especially in a context of increased hybrid working. Working from home (WFH) has become a realistic option for a substantial share of Dutch workers [10], [11], yet disruption studies still predominantly focus on realised travel responses, such as rerouting and mode switching. As a result, non-travel adaptation is often weakly observed, implicitly treated, or folded into residual demand reduction. This matters because WFH availability fundamentally changes the commuter choice set during temporary disruption. At the same time, the existing evidence base is not fully suited to ex ante roadworks appraisal. Many studies are tied to single disruption events, making severity difficult to separate from the surrounding context, and recent Dutch evidence indicating that higher travel-time burdens can reduce car use does not explicitly model WFH as a distinct commuter response under temporary roadworks [12]. In practice, roadworks appraisal and modelling therefore still often rely on simplified demand-reduction assumptions or ad hoc behavioural corrections, while work-related constraints and explicit non-travel responses remain weakly represented [13].

The objective of this paper is to examine how the severity of temporary roadworks reshapes commuter adaptation in the Netherlands, with particular attention to the extent to which substitution away from routine car commuting is absorbed by public transport (PT) and working from home under different work-related constraints. The analysis is based on an online survey among working commuters and combines an attribute-based stated-choice experiment, a commute-time-pivoted stated-choice experiment, and a revealed-preference module on experienced major disruptions. This design allows both general trade-offs and severity-conditioned responses to be examined while maintaining a connection to realised behaviour.

This paper contributes in three ways. First, it treats WFH as an explicit behavioural response to temporary roadworks rather than as a residual component of disappearing traffic. Second, it shows that adaptation to disruption severity is non-linear: minor increases in travel burden often remain within a tolerance range, whereas more substantial disruption triggers markedly stronger substitution away from the car. Third, it demonstrates that disruption severity alone does not determine the response channel; instead, work-related constraints, especially WFH feasibility and on-site obligations, strongly shape whether adaptation occurs through continued car use, PT switching, or WFH. The paper, therefore, addresses not only whether commuters adapt to temporary roadworks but also how disruption severity and work-related constraints jointly determine the channel through which that adaptation occurs. The remainder of this paper is structured as follows. Section II develops the conceptual framework. Section III describes the data and methodology. Section IV presents the results. Section V discusses the findings and their implications, and Section VI concludes.

II. Conceptual Framework

A. Adaptation channels under temporary roadworks

Behavioural responses to temporary roadworks can be understood as a set of possible adaptation channels rather than as a single adjustment. Previous research on planned and unplanned road disruption shows that travellers may respond through intramodal adaptations, such as rerouting or retiming, through intermodal substitution, or by suppressing the trip altogether [4]–[7]. This implies that disruption does not automatically translate into a uniform reduction in traffic demand. Instead, travellers may attempt to preserve habitual travel behaviour for as long as feasible and only shift to broader forms of adaptation when the burden of the disruption becomes sufficiently high.

For commuting trips, not all possible responses are equally relevant for the study. The focus of this paper is on the adaptation channels that most directly preserve, replace, or remove routine car commuting under temporary roadworks. Three alternatives are therefore central: continuing to commute by car, switching to PT, and avoiding the commute by working from home. Continuing by car reflects persistence of the habitual commute despite disruption. Switching to PT represents intermodal substitution, in which travel still takes place but through another mode. WFH constitutes a non-travel response because no commute is made on the disrupted day.

This distinction is conceptually important because the three channels have different implications for roadworks impacts and appraisal. Continued car use preserves demand on the road network, PT switching redistributes demand to another part of the transport system, and WFH removes the trip from the network altogether. The paper, therefore, does not attempt to represent the full spectrum of disruption responses but instead focuses on the alternatives most directly relevant to understanding how temporary roadworks reshape commuter demand away from routine car use.

B. Severity and work-related constraints

The central mechanism considered in this paper is that disruption severity creates pressure to adapt but, on its own, does not determine adaptation outcomes. As roadworks become more disruptive, the generalised burden of continuing the habitual car commute increases, making alternative responses more attractive. In the study, severity is conceptualised primarily as an increase in the travel burden of routine car commuting, operationalised through additional car travel time. This framing is appropriate because temporary roadworks most directly affect commuters by increasing delays, lengthening travel times, and reducing the reliability of the usual route.

However, the relationship between severity and behavioural response is not expected to be linear or uniform [14]–[16]. Minor increases in travel burden may remain within a tolerance range, allowing travellers to maintain their routine commute. More substantial increases are more likely to trigger adaptation. Even then, the resulting response channel depends not only on the level of disruption but also on the feasibility and attractiveness of the available alternatives. In this respect, PT and WFH represent fundamentally different forms of substitution. PT remains a travel-based response and is therefore shaped by accessibility, service availability, and the perceived burden of changing mode. WFH, by contrast, suppresses the commute altogether and depends on whether work can realistically be performed remotely.

This makes work-related constraints central to the behavioural process. In a context of increased hybrid working, WFH has become a plausible adaptation channel for a substantial share of workers [10], [11]. At the same time, it is not universally available. The ability to work from home, the extent to which workers must be physically present, and employer or task-related requirements all constrain whether WFH can be used as a response to disruption [17]–[19]. The conceptual proposition underlying this paper is therefore that increasing severity raises the likelihood of adaptation away from routine car commuting, while work-related constraints strongly shape whether that adaptation occurs through continued car use, PT switching, or WFH.

C. Operationalisation

The conceptual framework developed above guides the empirical design of the paper. First, it motivates defining the commuter choice set around the three adaptation channels of interest: car, PT, and WFH. Second, it identifies disruption severity as the core explanatory mechanism and work-related constraints as the main conditioning factors that shape response channel selection. Third, it implies that the study should distinguish between general stated trade-offs and responses to severity levels that are anchored more closely to the respondent's own commute.

In the study, this framework is operationalised through two stated-choice components and one revealed-preference component. The attribute-based stated-choice experiment captures general trade-offs among the three adaptation channels in stylised temporary roadwork scenarios. The pivot stated-choice experiment anchors disruption severity to respondents' reported car commute times by imposing percentage increases in car travel time. This allows the analysis to examine whether higher levels of disruption trigger stronger substitution away from routine car commuting. The revealed-preference module provides a complementary perspective by asking car commuters about realised responses to experienced major disruption.

Work-related constraints are explicitly incorporated into this design. In particular, the survey measures whether respondents can work from home and whether they must be on-site for work, allowing the analysis to test whether WFH serves as a broadly available substitute or a constrained response channel. The conceptual framework, therefore, serves as the basis for the empirical strategy in the following section, where the survey design, sample, and modelling approach are described in more detail.

III. Data and Methodology

A. Survey and experimental design

The empirical analysis is based on an online survey administered through Qualtrics among working commuters in the Netherlands. The survey was designed to examine how temporary roadworks affect adaptation away from routine commuting, with particular attention to the roles of PT and WFH. After providing informed consent, respondents completed questions on socio-demographic characteristics, work organisation, WFH possibilities, and normal commuting behaviour. They were then presented with the stated-choice (SC) components of the survey, followed by a short revealed-preference (RP) module for eligible respondents.

The survey combined two complementary SC components. The first was an attribute-based SC experiment designed to capture general trade-offs between continuing by car, switching to PT, and WFH under stylised temporary roadworks scenarios. To limit respondent burden, the design was divided into two blocks of six choice tasks, and each respondent was randomly assigned to one of the blocks. The second component was a pivot SC experiment targeted at respondents who normally commute by car and have a car available. In this module, disruption severity was anchored to the respondent's reported car commute time and represented as travel-time increases of 25%, 45%, and 60%. This enabled the analysis of severity-conditioned responses in a setting closer to the respondent's commuting context. The same car-commuter group also received a short RP module on realised responses to experienced major disruption. Overall, this design allowed the analysis to combine stylised behavioural trade-offs, commute-specific severity responses, and a limited reality check based on self-reported realised behaviour. Stated-choice methods are appropriate in this context because they allow controlled variation in disruption attributes and the inclusion of alternatives, such as WFH, that are difficult to observe systematically under comparable real-world conditions [20]–[23]. The pivoted component increases contextual realism by anchoring hypothetical disruption levels to respondents' own reported commute conditions [24], [25]. The severity framing was not chosen arbitrarily. In the underlying thesis, Dutch roadworks records from the National Data Warehouse for Traffic Information (NDW) were analysed to characterise the timing, duration, and hindrance patterns of temporary roadworks, while an OMNITRANS case study of the A4 De Hoek–Burgerveen corridor was used to translate a representative high-impact intervention into plausible additional car travel-time penalties. The pivot severity levels of 25%, 45%, and 60% were selected on that basis: 25% represents a moderate but noticeable increase, 45% reflects substantial disruption consistent with the upper range of the modelled impacts, and 60% captures very severe conditions. Using non-equidistant levels also avoids imposing linearity in the behavioural response to disruption severity.

B. Sample and descriptive context

The final analytical sample consisted of 180 respondents after applying standard quality and plausibility filters to the Qualtrics survey data. This sample is suitable for identifying behavioural mechanisms within the observed respondent group, but it should not be interpreted as representative of the wider Dutch commuter population.

Table I summarises the main socio-demographic characteristics of the cleaned analytical sample. The sample is skewed towards younger, more highly educated, and more Randstad-based respondents, and should therefore not be interpreted as representative of the wider Dutch commuter population. These distortions are important when interpreting subgroup prevalence and aggregate choice shares, especially because such characteristics are likely to correlate with work flexibility, WFH feasibility, and mode preferences. The strongest inference from the dataset therefore, concerns behavioural structure and heterogeneity rather than population-level switching rates.

Table II summarises the work organisation, WFH, and commuting context most relevant for interpreting the stated-choice and pivot results. The sample is characterised by relatively high levels of WFH feasibility and work flexibility. In the cleaned sample, 42.8% report that they can work from home almost always, 45.0% report that WFH is possible but limited, and only 12.2% indicate that WFH is not possible. The sample also shows substantial variation in normal commuting mode: 45.0% travel by car, 27.2% by PT, and 27.8% by walking or cycling. Among respondents for whom WFH is feasible

TABLE I
SAMPLE COMPOSITION OF THE CLEANED ANALYTICAL SAMPLE (%, $N = 180$).

Category	Sample (%)
Gender	
Male	61.1
Female	31.7
Other / prefer not to say	7.2
Age	
18–24	15.0
25–34	46.1
35–44	18.9
45–54	9.4
55–64	10.0
65+	0.6
Education	
MSc+	45.0
HBO	28.3
BSc	12.2
MBO	9.4
Secondary / other	5.0
Residence	
Randstad	59.4
Not Randstad	40.6

to some extent, fixed on-site obligations remain common, which supports the paper's focus on work-related constraints as a determinant of behavioural adaptation. Overall, these descriptives indicate a sample with relatively high workplace flexibility, but not one in which WFH is unconstrained or universally available.

TABLE II
WORK, WFH, AND COMMUTING CONTEXT IN THE CLEANED SAMPLE (%).

Item	%
WFH feasibility	
Almost always	42.8
Limited	45.0
Not possible	12.2
Main commute mode	
Car	45.0
PT	27.2
Walk/Bike	27.8
Work flexibility	
Largely flexible	55.1
Somewhat flexible	41.1
Fixed hours/location	3.8
Fixed office days	
None	31.6
1 day/week	32.3
2 days/week	20.3
3 days/week	9.5
4 days/week	6.3
5 days/week	0.0
Actual WFH days/week	
0 days	18.4
1 day	38.0
2 days	29.1
3 days	12.7
4 days	1.3
5 days	0.6

Note: Percentages for work flexibility, fixed office days, and actual WFH days are based on respondents for whom WFH was feasible to some extent ($N = 158$).

C. *Modelling approach*

The stated-choice responses were analysed within a random utility framework. Panel multinomial logit (MNL) models were first estimated as a transparent baseline for the attribute-based experiment. To account for heterogeneity in behavioural sensitivities, the analysis was then extended using mixed logit (MXL) and latent class (LC) specifications. The mixed logit models capture unobserved taste variation through random parameters, while the latent class models identify discrete behavioural segments with systematically different response patterns. Because each respondent completed multiple-choice tasks, the models were estimated in panel form so that the sequence of choices made by the same individual was treated consistently. These model classes are standard tools in transport choice analysis and are well-suited to studying heterogeneity, inertia, and repeated observations in behavioural response data [21], [26], [27].

Model specifications were selected using a parsimonious and behaviourally interpretable approach. For the baseline stated-choice analysis, panel MNL models were used as transparent benchmark specifications. Mixed Logit and Latent Class models were then estimated to assess whether the average response concealed meaningful heterogeneity in car time sensitivity and baseline WFH propensity. In the pivot analysis, alternative functional forms for delay were tested, after which a log-delay specification with a low-delay tolerance term and work-related WFH constraints was retained as the preferred specification. The preferred models are therefore reported not only because they improved fit, but because they best matched the paper's substantive objective of identifying non-linearity, constraint-gated WFH responses, and interpretable behavioural heterogeneity.

The pivot experiment was analysed separately using panel MNL specifications to capture non-linear severity responses. The preferred specification models the effect of additional delay using a log transformation and includes a tolerance indicator for the low-disruption condition. To reflect the conceptual framework developed in the previous section, WFH utility was additionally conditioned on work-related constraints, in particular, whether respondents could work from home and whether they needed to be physically present at work. The RP module was not used to estimate severity elasticities directly, as the realised disruptions were not observed under comparable, controlled severity conditions. Instead, it was used as a behavioural benchmark to compare stated intentions with self-reported realised responses.

IV. RESULTS

A. *Baseline stated-choice trade-offs and the role of constraints*

This subsection presents the baseline stated-choice results to establish the general trade-offs underlying commuter adaptation to temporary roadworks. The benchmark panel multinomial logit model in Table III provides a first indication that continued car commuting becomes less attractive as the burden of the car trip increases, while the attractiveness of alternative responses depends strongly on their baseline appeal and feasibility. The results provide a behavioural benchmark before turning to the more explicit severity evidence from the pivot experiment.

The estimated coefficients show that both car travel time and car cost significantly reduce the utility of continuing by car. In contrast, the coefficient for PT travel time is not statistically significant in this benchmark specification, while the alternative-specific constant for PT is strongly negative. This suggests that PT is not rejected solely because of marginal travel-time differences, but rather because it faces a substantial baseline barrier relative to routine car use, which is consistent with literature showing that mode switching towards PT depends on a broader set of service, interchange, and habit-related barriers. A similar pattern holds for WFH. Although WFH is conceptually available as a non-travel response, its large negative alternative-specific constant indicates that it is not a default choice in the absence of enabling conditions.

TABLE III
BENCHMARK PANEL MNL (SC_BASE + WFH FEASIBILITY): ROBUST PARAMETER ESTIMATES. TIME IS SCALED PER 10 MINUTES; CAR COST PER €10.

Parameter	Estimate	Rob. SE	t-stat	p-value
ASC_{WFH}	-9.33	1.06	-8.76	< 0.001
ASC_{PT}	-7.65	1.47	-5.21	< 0.001
$\beta_{\text{Cost, Car}}$	-2.41	0.48	-5.00	< 0.001
$\beta_{\text{Time, Car}}$	-0.97	0.09	-10.50	< 0.001
$\beta_{\text{Time, PT}}$	-0.16	0.15	-1.05	0.294
$\beta_{\text{on-site, Medium}}$	-1.63	0.19	-8.81	< 0.001
$\beta_{\text{on-site, High}}$	-3.70	0.48	-7.64	< 0.001
$\delta_{\text{WFH, Feasible}}$	1.92	0.48	4.00	< 0.001

The strongest conditioning effects in the benchmark model are work-related constraints. Medium and high on-site obligations both have large, statistically significant negative effects on WFH utility, with the penalty increasing sharply as physical presence becomes more necessary. By contrast, WFH feasibility has a strong positive effect, indicating that the option to work remotely materially increases the probability that commuters substitute away from their routine car commute through WFH. Taken together, these results support the paper's central conceptual proposition: adaptation is not driven solely by disruption burden, but is strongly channelled by the feasibility of available alternatives.

Figure 1 illustrates the behavioural implications of this benchmark model for an average commuter profile with WFH feasibility. As the delay increases, the predicted probability of continuing by car declines, while the probabilities of both PT and WFH increase. However, the increase is not distributed evenly across the alternatives. WFH absorbs a substantial share of the adaptation response once delay becomes more salient, whereas PT remains a secondary substitute despite rising relative attractiveness. This pattern reinforces two points that are central to the remainder of the paper. First, increasing disruption creates pressure to move away from routine car commuting. Second, the main outlet of that pressure is shaped by constraint-gated alternatives rather than by a uniform shift across all available modes.

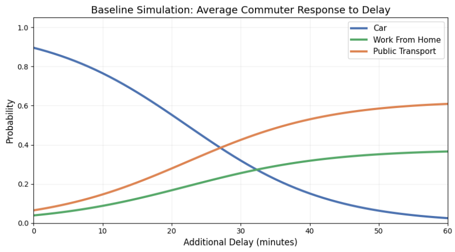


Fig. 1. Baseline simulation: Predicted probability of mode choice under increasing delay for an average commuter (Car base time: 41 min; Cost: €8.00; WFH feasible).

These baseline stated-choice results already suggest that commuter adaptation under temporary roadworks is structured and selective rather than uniform. However, they do not yet show whether this adaptation pattern unfolds gradually or through sharper threshold-like shifts across clearly defined severity levels. The pivot experiment addresses this more directly by anchoring severity to the respondent's own car commute and is therefore discussed next.

B. *Non-linear severity response in the pivot experiment*

The pivot experiment provides the most direct evidence on how commuters respond to increasing roadworks severity. Unlike the baseline stated-choice experiment, which captures general trade-offs under stylised disruption scenarios, the pivot design anchors disruption severity to respondents' reported car commutes. This makes it possible to examine more directly whether higher levels of disruption trigger stronger substitution away from routine car commuting.

Table IV reports the observed choice shares across the three disruption levels, while Fig. 2 visualises the same pattern. The results show a strongly non-linear response. Under the low-severity condition, corresponding to a 25% increase in car travel time, 92.6% of respondents still choose to continue by car. At this level, WFH remains limited to 7.4%, while no respondents chose PT. This suggests that relatively small increases in travel burden often remain within a tolerance range in which the habitual car commute is preserved.

TABLE IV
OBSERVED CHOICE SHARES BY DISRUPTION LEVEL.

Disruption Level	Car Share	PT Share	WFH Share
Low (25%)	92.6%	0.0%	7.4%
Medium (45%)	53.1%	17.3%	29.6%
High (60%)	29.6%	22.2%	48.1%

At the medium-severity level, where car travel time increases by 45%, car persistence drops sharply to 53.1%. This decline is accompanied by a substantial increase in both WFH and PT, which rise to 29.6% and 17.3%, respectively. At the high-severity level of 60%, this pattern becomes even more pronounced: the share of respondents choosing car falls further to 29.6%, while WFH becomes the dominant adaptation channel at 48.1%. PT also increases to 22.2%, but remains a secondary substitute relative to WFH.

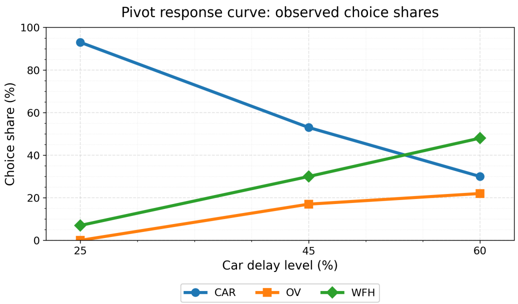


Fig. 2. Observed pivot choice shares by severity level.

These observed shares already point to two important conclusions. First, adaptation away from routine car commuting is clearly not linear in disruption severity. The behavioural shift between the low- and medium-severity conditions is much larger than would be expected under a simple proportional response. Second, the increase in adaptation is not absorbed uniformly across the alternatives. As disruption intensifies, WFH emerges as the dominant substitute, while PT also gains share, though to a lesser extent. In a context where remote work is feasible for part of the sample, non-travel adaptation therefore appears to absorb a larger share of roadworks pressure than intermodal substitution.

The model estimates in Table V support this interpretation more formally. Both PT and WFH have strongly negative alternative-specific constants, indicating that neither option is a default response in the absence of additional disruption pressure or enabling conditions. At the same time, the preferred pivot specification indicates a large, positive tolerance effect for the low-disruption condition. This suggests that respondents derive additional utility from preserving their habitual car commute when the increase in travel time is still perceived as relatively limited.

TABLE V
PIVOT MNL ESTIMATION RESULTS (PREFERRED SPECIFICATION).

Parameter	Estimate	Rob. SE	t-stat	Sig.
ASC_{PT}	-6.50	1.40	-4.65	***
ASC_{WFH}	-5.69	1.51	-3.77	***
$\beta_{\mathrm{Tolerance}}$ (LowDelay)	2.02	0.47	4.29	***
$\beta_{\log}$ (Time sensitivity)	-1.87	0.46	-4.09	***
$\beta_{\mathrm{Location}}$ (Must on Loc)	-3.26	1.16	-2.82	**
$\beta_{\mathrm{WFH,\ Feasible}}$	2.26	1.05	2.16	*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Conditional on moving beyond this low-disruption regime, the log-transformed delay coefficient is negative and highly significant, confirming that stronger increases in car travel time reduce the attractiveness of continuing by car. The model also reinforces the importance of work-related constraints. Having to be on location for work strongly decreases the utility of WFH, whereas WFH feasibility increases it. This means that increasing severity does not mechanically translate into a single dominant behavioural response. Instead, the direction of substitution depends on whether commuters can realistically make use of the non-travel option.

Figure 3 further illustrates this threshold-like pattern. At relatively low levels of absolute delay, the predicted probability of switching remains limited, indicating that commuters tend to absorb modest disruption while preserving their routine car commute. This range can be interpreted as a tolerance zone in which behavioural inertia is still dominant. Beyond this zone, however, the probability of switching increases much more rapidly, indicating that adaptation pressure does not build up linearly. Instead, once disruption becomes sufficiently salient, substitution towards PT or WFH accelerates markedly. This graphical pattern is consistent with both the observed pivot shares and the positive tolerance parameter in the preferred pivot model.

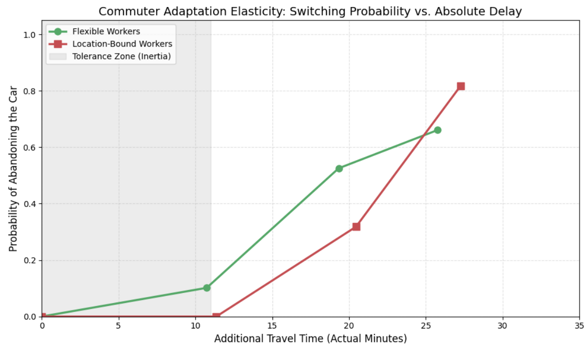


Fig. 3. Threshold-like adaptation pattern in the pivot experiment. The figure shows the predicted probability of switching to an alternative (PT or WFH) as a function of absolute delay. The shaded area represents a tolerance zone in which behavioural inertia remains dominant.

Taken together, the observed shares, the preferred pivot model, and the elasticity figure provide the clearest support for the central mechanism proposed in this paper. Increasing roadworks severity creates adaptation pressure, but that pressure is mediated by tolerance at low disruption levels and channelled by work-related constraints as disruption becomes more substantial. In this setting, WFH emerges as the main substitute when feasible, while PT remains relevant but secondary. The next subsection examines whether these average patterns mask meaningful heterogeneity across commuters.

C. Heterogeneity in adaptation

The average response patterns presented above do not imply that all commuters react to disruption in the same way. A central question is therefore whether the estimated adaptation effects reflect a broadly shared behavioural pattern or mask meaningful variation across respondents. The results from the mixed logit and latent class analyses indicate substantial heterogeneity, both in sensitivity to additional car travel time and in baseline propensity to use WFH as an adaptation channel.

Table VI reports the preferred mixed logit specification. The estimated mean effect for car travel time is negative and highly significant, confirming that, on average, increasing car travel time reduces the utility of continuing the routine car commute. More importantly, the corresponding standard deviation is also large and highly significant, indicating that this sensitivity varies strongly across respondents. A similar pattern is found for the WFH alternative-specific constant: the mean is strongly negative, but the significant standard deviation shows that the baseline propensity to use WFH differs considerably across commuters. This provides formal evidence that average response parameters conceal important behavioural variation.

TABLE VI
PARAMETER ESTIMATES FOR THE PREFERRED MIXED LOGIT MODEL (MXL 4). RANDOM PARAMETERS ARE DEFINED BY A MEAN (μ) AND STANDARD DEVIATION (σ).

Parameter	Estimate	Rob. SE	t-stat	p-value
Random Parameters				
$\mu_{\text{Time,Car}}$	-2.13	0.24	-8.92	< 0.001
$\sigma_{\text{Time,Car}}$	0.50	0.06	8.70	< 0.001
$\mu_{\text{ASC,WFH}}$	-18.62	2.00	-9.30	< 0.001
$\sigma_{\text{ASC,WFH}}$	2.11	0.28	7.47	< 0.001
Fixed Parameters				
$\beta_{\text{Cost,Car}}$	-4.50	0.82	-5.46	< 0.001
ASC_{PT}	-15.62	2.62	-5.96	< 0.001
$\beta_{\text{time,pt}}$	-0.29	0.24	-1.18	0.238
$\beta_{\text{on-site, Medium}}$	-2.72	0.36	-7.57	< 0.001
$\beta_{\text{on-site, High}}$	-5.72	0.63	-9.15	< 0.001
$\delta_{\text{WFH,possible}}$	3.26	0.77	4.25	< 0.001

The fixed parameters in the mixed logit model also reinforce the earlier findings from the benchmark and pivot analyses. Car cost significantly reduces the attractiveness of continuing by car, while PT again faces a strongly negative baseline propensity. WFH remains highly dependent on work-related constraints: medium and high on-site obligations both substantially reduce its utility, whereas WFH feasibility increases it. The main additional insight is therefore not a change in the overall direction of effects, but a clearer demonstration that commuters differ considerably in how strongly they respond to these trade-offs.

To translate this heterogeneity into a more interpretable behavioural structure, the latent class analysis identifies two broad response profiles. A two-class specification was retained because it provided the most behaviourally coherent and parsimonious segmentation for interpretation in the paper. As illustrated in Fig. 4, one class is more delay-sensitive and shows a lower baseline propensity to use WFH, whereas the other is more delay-tolerant and has a higher baseline propensity to adapt through WFH under the same trip conditions. The figure shows that the probability of continuing by car declines much more rapidly for the delay-sensitive class as delay increases, while the delay-tolerant class maintains a higher car-choice probability across the same range of disruption levels.

This segmented interpretation is consistent with the paper's broader results. It suggests that the behavioural response to

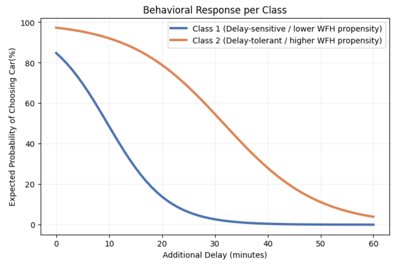


Fig. 4. Behavioural heterogeneity: Predicted car-choice probability for Class 1 (delay-sensitive / lower WFH propensity) versus Class 2 (delay-tolerant / higher WFH propensity) under identical trip constraints (Base time: 41 min; Cost: €8.00).

temporary roadworks is not only non-linear on average, but also unevenly distributed across the commuter population. Some commuters are relatively quick to move away from routine car use as disruption intensifies, whereas others remain more tolerant of additional burden or are structurally less inclined to use WFH. In substantive terms, this means that severity creates adaptation pressure, but that both the magnitude and the channel of adaptation vary systematically across commuters.

Taken together, the mixed logit and latent class results show that population-average response functions provide only a partial picture of commuter adaptation under temporary roadworks. They capture the overall direction of behavioural change, but obscure meaningful differences in delay sensitivity and baseline WFH propensity. This reinforces the need to interpret the results not as a single homogeneous demand response, but as a structured pattern of heterogeneous adaptation. The final subsection, therefore, turns to the revealed-preference evidence to examine how these stated patterns compare with self-reported realised behaviour.

D. Revealed behaviour and the intention–behaviour gap

The revealed-preference module provides a limited but important reality check on the stated-choice findings. Unlike the stated experiments, the observed responses were not under controlled, comparable-severity conditions. The module, therefore, cannot be used to estimate severity-specific elasticities directly. Instead, it is used to assess whether the general behavioural patterns identified in the stated-choice analysis are broadly consistent with self-reported realised responses to experienced major disruption.

Figure 5 shows the observed behavioural responses among car commuters who reported having experienced major disruption. The dominant realised response is to continue commuting by car, while smaller shares report adapting through WFH or PT. This confirms that adaptation does occur in practice, but also suggests that real-world car persistence is stronger than the stated-choice scenarios alone would imply.

This difference should not be interpreted as a contradiction between the stated and revealed evidence. Rather, it points to an intention-behaviour gap that is plausible in the context of temporary roadworks. Real-world responses are shaped

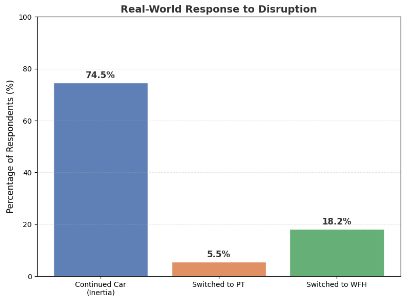


Fig. 5. Observed behavioural responses to experienced major disruption among car commuters.

by uncertainty, habits, imperfect information, and practical constraints that are more difficult to reproduce in controlled stated-choice settings. This interpretation is consistent with the external validity and hypothetical bias literature, which shows that stated responses can deviate materially from realised behaviour because of simplified decision settings, imperfect consequentiality, and respondent uncertainty. As a result, the stated-choice results are most informative about the direction and structure of behavioural adaptation as severity increases, whereas the revealed-preference evidence suggests that realised switching magnitudes are likely to be more muted.

The RP evidence therefore strengthens the interpretation of the earlier results in two ways. First, it supports the conclusion that adaptation away from routine car commuting is real and behaviourally meaningful. Second, it cautions against reading stated substitution rates as direct forecasts of realised behaviour under actual roadworks. The most robust conclusion is thus not the exact magnitude of switching, but the underlying pattern: higher disruption severity increases adaptation pressure, while real-world inertia and constraints dampen the extent to which that pressure translates into observed behavioural change.

V. Discussion

The results of this paper suggest that commuter adaptation to temporary roadworks is best understood as a threshold-like and channel-dependent process rather than as a uniform reduction in car travel. Across the stated-choice evidence, increasing disruption severity reduces the attractiveness of preserving the routine car commute, but this effect is not linear. The pivot results indicate that relatively modest increases in travel burden are often absorbed within a tolerance range, whereas more substantial disruption triggers a much stronger shift away from routine car use.

At the same time, the results show that the key behavioural question is not only whether commuters adapt, but through which channel adaptation occurs. In the present study, working from home emerges as the most important substitute when feasible, while public transport plays a secondary but still meaningful role. This implies that adaptation away from car use under roadworks is not equivalent to a simple mode shift. Instead, disruption reallocates behaviour across continued car use, intermodal substitution, and non-travel adaptation.

A central implication of these findings is that work-related constraints are not peripheral modifiers, but core determinants of the adaptation process. WFH becomes behaviourally relevant only when commuters can realistically work remotely and are not strongly constrained by on-site obligations. The behavioural effect of temporary roadworks, therefore, depends not only on the severity of the disruption itself, but also on the institutional and occupational context in which commuters make their choices.

The heterogeneity results reinforce this interpretation. Adaptation is not distributed evenly across commuters: some are much more delay-sensitive, whereas others remain more tolerant of disruption or are less inclined to substitute through WFH. The revealed-preference evidence adds a further qualification by showing stronger real-world car persistence than the stated scenarios alone would suggest. Taken together, the results provide the strongest evidence for an underlying behavioural mechanism: increasing roadwork severity creates adaptation pressure, but tolerance, feasibility, and commuter heterogeneity determine whether and how that pressure translates into observed change.

A. Implications

These findings have direct implications for how temporary roadworks are represented in transport analysis and appraisal. First, behavioural responses should not be represented by a single, uniform demand-reduction factor. The evidence instead points to distinct disruption regimes: low levels of additional burden may remain within a tolerance range, whereas moderate-to-high levels trigger much stronger substitution away from routine car use. For ex ante roadworks appraisal, this suggests that severity should be represented using a small number of differentiated scenario tiers rather than through a single linear assumption.

Second, the results indicate that working from home should be treated as an explicit, constraint-driven response channel rather than absorbed into an undefined residual category of disappearing traffic. In practical terms, this means that demand reduction should be interpreted partly as the result of work-related flexibility rather than solely as a transport-system response. Appraisal and modelling frameworks may therefore benefit from distinguishing between commuter groups with higher and lower WFH feasibility or stronger on-site obligations.

Third, the findings suggest that public transport should not be treated as an automatic substitute for marginal increases in car travel time. In the present study, PT becomes more relevant as disruption intensifies, but its uptake remains bounded by baseline resistance and feasibility constraints. This implies that PT-related mitigation should be interpreted in a barrier-oriented manner: stronger PT uptake cannot be inferred solely from relative travel-time changes.

Finally, the observed intention-behaviour gap between stated and revealed evidence suggests that ex ante behavioural forecasts should be interpreted cautiously. The strongest evidence concerns the direction and structure of adaptation, rather than precise realised switching rates. For practical appraisal, this suggests that behavioural responses to roadworks are better reported as plausible ranges than as exact point estimates.

B. Limitations

Several limitations are important when interpreting the results. First, the core severity evidence is based on stated-choice experiments. This design is well-suited to identifying behavioural trade-offs and isolating the role of disruption severity, but it does not observe realised behaviour under comparable real-world roadworks conditions. The results should therefore be interpreted primarily as evidence on behavioural structure and direction rather than as exact forecasts of realised switching magnitudes.

Second, the analytical sample is not representative of the wider Dutch commuter population. It is relatively young, highly educated, and characterised by comparatively high levels of work flexibility and WFH feasibility. As a result, the estimated role of WFH may be stronger than would be expected in a more representative commuter sample.

Third, the empirical choice set is deliberately restricted to continued car use, PT, and WFH. This supports the paper's focus on substitution away from routine car commuting, but it also means that other relevant responses, such as rerouting, retiming, or destination changes, are not modelled explicitly. Future research could strengthen the evidence base by combining stated and revealed data under more comparable severity conditions, extending the choice set to include key intramodal responses, and incorporating richer PT and work-constraint measures.

VI. Conclusion

This paper examined how the severity of temporary roadworks reshapes commuter adaptation in the Netherlands, with particular attention to whether substitution away from routine car commuting occurs through public transport or working from home. The results show that this adaptation is not uniform. Instead, disruption severity creates pressure to move away from the habitual car commute, but the response is non-linear and strongly conditioned by work-related constraints. Modest increases in travel burden are often tolerated, whereas more substantial disruption leads to markedly stronger substitution. When feasible, working from home emerges as the main alternative, while public transport plays a secondary but meaningful role.

The main contribution of the paper is therefore the identification of a behavioural mechanism rather than a precise forecast of realised switching magnitudes. Temporary roadworks should not be represented as producing a single residual demand reduction. Rather, their effects depend on disruption severity, commuter heterogeneity, and the feasible adaptation channels available to different groups. For roadworks appraisal and modelling, this implies that behavioural response should be treated as channel-specific, constraint-sensitive, and likely better represented as severity-differentiated ranges than as uniform point assumptions.

References

[1] ANWB, "8 procent meer files op de nederlandse wegen in 2024," *ANWB*, Dec. 2024. [Online]. Available: https://www.anwb.nl/verkeer/nieuws/nederland/2024/december/filezwaarte-2024

[2] ANWB-verkeersinformatie, "Filezwaarte in september fors toegenomen," Oct. 2025. [Online]. Available: https://www.anwb.nl/verkeer/nederland/verkeersinformatie/filezwaarte

[3] Ministerie van infrastructuur en waterstaat, "Groot onderhoud wegen en vaarwegen," Sep. 2025. [Online]. Available: https://www.rijkswaterstaat.nl/over-ons/onze-organisatie/groot-onderhoud

[4] L. Ye, P. L. Mokhtarian, and G. Circella, "Commuter impacts and behavior changes during a temporary freeway closure: the 'Fix I-5' project in Sacramento, California," *Transportation Planning and Technology*, vol. 35, no. 3, pp. 341–371, Apr. 2012. [Online]. Available: http://www.tandfonline.com/doi/abs/10.1080/03081060.2012.673270

[5] M. Yun, D. Herick, and P. Mokhtarian, "Nonwork Travel Behavior Changes During Temporary Freeway Closure: The Fix I-5 Project in Sacramento, California," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2231, pp. 1–9, Dec. 2011.

[6] S. Zhu, D. Levinson, H. X. Liu, and K. Harder, "The traffic and behavioral effects of the I-35W Mississippi River bridge collapse," *Transportation Research Part A: Policy and Practice*, vol. 44, no. 10, pp. 771–784, Dec. 2010. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0965856410000923

[7] J. Desai, B. Scholer, J. K. Mathew, H. Li, and D. M. Bullock, "Analysis of Route Choice During Planned and Unplanned Road Closures," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 3, pp. 489–502, 2022. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9797882

[8] S. Cairns, S. Atkins, and P. Goodwin, "Disappearing traffic? The story so far," 2001.

[9] T. Calvert and S. Melia, "Does traffic really disappear when roads are closed?" *Proceedings of the Institution of Civil Engineers - Municipal Engineer*, vol. 176, no. 1, pp. 1–9, Jan. 2023. [Online]. Available: https://www.sciencedirect.com/org/science/article/abs/pii/S1751769923000049

[10] Centraal Bureau voor de Statistiek (CBS). (2024) Ruim helft nederlanders werkt weleens thuis. [Online]. Available: https://www.cbs.nl/nl-nl/nieuws/2024/11/ruim-helft-nederlanders-werkt-weleens-thuis

[11] L. Ashour and Q. Shen, "Unveiling post-pandemic commute choices amidst the rise of telework," *Transportation Research Part D: Transport and Environment*, vol. 149, p. 105068, Dec. 2025. [Online].

Available: https://www.sciencedirect.com/science/article/pii/S136192092500478X

[12] R. van Dijk, "The causation of disappearing traffic in the context of the Netherlands," Master's thesis, 2022. [Online]. Available: https://studenttheses.uu.nl/bitstream/handle/20.500.12932/43115/The%20causation%20of%20disappearing%20traffic%20in%20the%20context%20of%20the%20Netherlands.pdf?sequence=1&isAllowed=y

[13] K. de Clercq, "Interview on planned roadworks, commuter adaptation, and modelling practice at sweco," Sep. 2025, personal interview, Sweco, September 2025.

[14] A. Obermeyer, M. Treiber, and C. Evangelinos, "On the identification of thresholds in travel choice modelling," *Journal of Choice Modelling*, vol. 17, pp. 1–9, 2015.

[15] M. He, S. Zhao, and M. He, "Tolerance threshold of commuting time: Evidence from kunming, china," *Journal of Transport Geography*, vol. 57, pp. 1–7, 2016.

[16] X. Di, H. X. Liu, S. Zhu, and D. M. Levinson, "Indifference bands for boundedly rational route switching," *Transportation*, vol. 44, no. 5, pp. 1169–1194, 2017. [Online]. Available: sciencedirect.com/science/article/abs/pii/S0965856411000498

[17] P. L. Mokhtarian and I. Salomon, "Modeling the desire to telecommute: The importance of attitudinal factors in behavioral models," *Transportation Research Part A: Policy and Practice*, vol. 31, no. 1, pp. 35–50, 1997.

[18] C. P. Peters, K. G. Tijdens, and C. Wetzels, "Employees' opportunities, preferences, and practices in telecommuting adoption," *Information & Management*, vol. 41, no. 4, pp. 469–482, 2004. [Online]. Available: https://www-sciencedirect-com.tudelft.idm.oclc.org/science/article/pii/S0378720603000855#aep-section-id44

[19] M. Walls, E. Safirova, and Y. Jiang, "What drives telecommuting? the relative impact of worker demographics, employer characteristics, and job types," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2010, no. 1, pp. 111–120, 2007. [Online]. Available: https://journals.sagepub.com/doi/10.3141/2010-13

[20] D. A. Hensher, "Stated preference analysis of travel choices: the state of practice," *Transportation*, vol. 21, no. 2, pp. 107–133, May 1994. [Online]. Available: https://doi.org/10.1007/BF01098788

[21] D. A. Hensher, J. M. Rose, and W. H. Greene, "Applied Choice Analysis," *Cambridge University Press*, 1 2005. [Online]. Available: https://doi.org/10.1007/9781316136232

[22] J. M. Rose and M. C. J. Bliemer, "Constructing efficient stated choice experimental designs," *Transport Reviews*, vol. 29, no. 5, pp. 587–617, 7 2009. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/01441640902827623

[23] S. Hess, "Some lessons in stated choice survey design," 2009.

[24] J. M. Rose and S. Hess, "Dual-Response Choices in Pivoted Stated Choice Experiments," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2135, no. 1, pp. 25–33, Jan. 2009. [Online]. Available: https://journals.sagepub.com/doi/10.3141/2135-04

[25] C. Rudloff and M. Straub, "Mobility surveys beyond stated preference: introducing MyTrips, an SP-off-RP survey tool, and results of two case studies," *European Transport Research Review*, vol. 13, no. 1, p. 49, Sep. 2021. [Online]. Available: https://doi.org/10.1186/s12544-021-00510-5

[26] V. Cantillo, J. De Dios Ortúzar, and H. C. W. L. Williams, "Modeling discrete choices in the presence of inertia and serial correlation," *www-jstor-org.tudelft.idm.oclc.org*, May 2007. [Online]. Available: https://www-jstor-org.tudelft.idm.oclc.org/stable/25769346

[27] H. Qin, J. Gao, H. Guan, and H. Chi, "Estimating heterogeneity of car travelers on mode shifting behavior based on discrete choice models," *Transportation Planning and Technology*, vol. 40, no. 8, pp. 914–927, Nov. 2017, publisher: Routledge _eprint: https://doi.org/10.1080/03081060.2017.1355886. [Online]. Available: https://doi.org/10.1080/03081060.2017.1355886

B

Ngene syntax

```
Design
;alts  = car, pt, tw
;rows  = 12
;block = 2
; eff   = (mnl,d)
;alg   = swap


; model:
U(car) = b_tt_car[-0.02] * tt_car[45,60,70]
       + b_tc_car[-0.1]  * tc_car[11,13,14]

U(pt)  = asc_pt[0]
       + b_tt_pt[-0.02] * tt_pt[50,55,60]

U(tw)  = asc_tw[0]
```

C

Ngene output

MNL Efficiency Measures

D-error	0.0668
A-error	0.293334
B-estimate	27.751322
S-estimate	322.410213

Priors and SP Estimates

	b_tt, car	b_tc, car	b_tt, pt
Fixed prior value	-0.02	-0.1	-0.02
SP estimate	122.227169	322.410213	269.057316
SP t-ratio	0.177285	0.109157	0.119491

Experimental Design

Choice situation	car.tt_car	car.tc_car	pt.tt_pt	Block
1	45	11	55	2
2	60	13	55	1
3	60	14	50	2
4	60	14	55	2
5	70	13	50	2
6	70	11	50	1
7	60	13	50	1
8	45	14	55	1
9	45	11	60	2
10	70	13	60	2
11	70	11	60	1
12	45	14	60	1

D

Blocking

Table D.1: Final SC Design with Context Variables

Task	Block	TW	Time	Car TT (min)	Car Cost (€)	PT TT (min)
1	1	3	1	45	14	60
2	1	1	2	60	14	55
3	1	2	2	70	11	50
4	1	1	1	70	13	50
5	1	2	3	60	13	55
6	1	3	3	45	11	60
7	2	2	1	70	11	60
8	2	2	3	60	13	50
9	2	3	2	45	11	55
10	2	3	1	45	14	55
11	2	1	3	60	14	50
12	2	1	2	70	13	60

E

Full survey design

E.1. Survey design

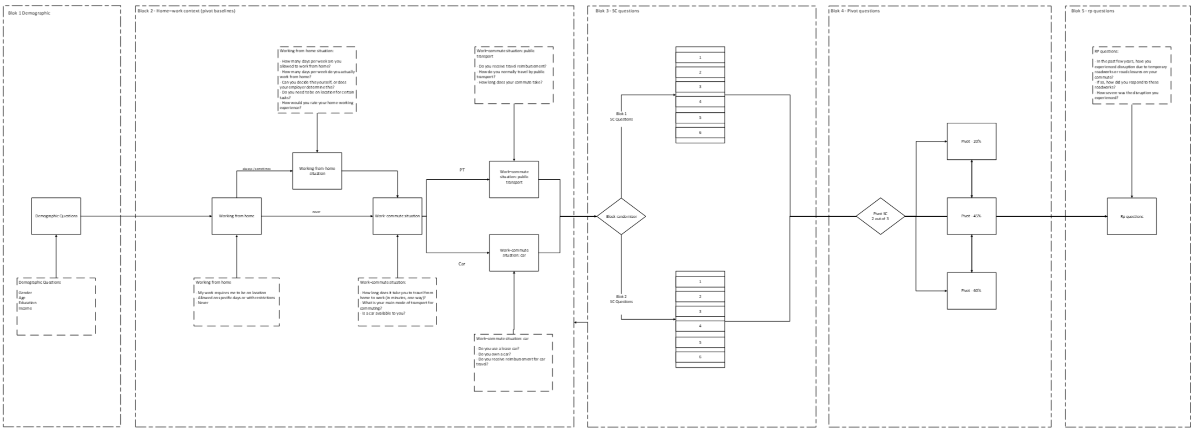


Figure E.1: Flowchart

E.1.1. Opening screen and informed consent

After clicking the survey link in the invitation, respondents are presented with an opening screen explaining the purpose of the study. The first block of questions records basic socio-demographic characteristics and the number of working days per week. These variables are used to describe the sample and to explore heterogeneity in behavioural responses. Table E.1 summarises the constructs and answer options.

E.1.2. Work and WFH characteristics

The next blocks focus on respondents' work situations and the structural possibilities for working from home. A filter question first asks whether the current job can be performed from home:

> *"Can your current work in principle be done from home?"*

with three response categories: almost always, only to a limited extent, and never. Respondents who answer that home-working is never possible skip the subsequent WFH situation block. For respondents with at least some possibility to work from home, the WFH situation block records employer agreements, actual WFH frequency and fixed office days. Table E.2 summarises these items.

These variables jointly measure both the formal opportunity to WFH and actual WFH habits, which are expected to influence the likelihood of choosing the home-working alternative in the SC experiment.

Table E.1: Socio-demographic and basic work characteristics collected in the survey.

Construct	Answer options
Gender	Man Woman Non-binary / other Prefer not to say.
Highest completed education	No formal education Primary education Secondary education (vmbo, havo or vwo) Upper secondary vocational education (MBO) Higher professional education (HBO) University bachelor University master or higher.
Age	Open question: age in years.
Driving licence (car)	Yes No Prefer not to say.
Residence in the Randstad	Yes No Prefer not to say.
Number of working days per week	1 day 2 days 3 days 4 days 5 days.

Table E.2: Questions on WFH situation for respondents with home-working possibilities.

Construct	Answer options
Number of days per week allowed to work from home	1, 2, 3, 4 or 5 days.
Number of days per week usually worked from home	0, 1, 2, 3, 4 or 5 days.
Fixed office days or days requiring physical presence	0, 1, 2, 3, 4 or 5 days per week.

E.1.3. Flexibility of working times and location

A separate block measures schedule and location flexibility. Respondents indicate to what extent they can adapt their working hours or location if needed with two questions:

- Can you adjust your working hours and/or work location if that suits you better?
- Does your work contain tasks that can only be performed on location?

These indicators are used as context variables to capture structural constraints on WFH and time-shifting behaviour.

E.1.4. Commuting situation and access to alternatives

The commuting block characterises respondents' usual commute on a normal working day and their access to transport alternatives. This block is shown to all respondents, regardless of their ability to work from home. Table E.3 summarises the questions and answer options.

These commuting variables are used both descriptively and as explanatory variables in the discrete choice models, for example, to differentiate between commuters who bear fuel and parking costs themselves and those who travel with a leased car.

Table E.3: Information on commuting situation and access to transport alternatives.

Construct	Answer options
Usual main mode on a normal workday	Car Public transport Walking or cycling.
Baseline travel time to work	Open question: travel time in minutes
Car availability	Yes No Prefer not to say.
Use of a lease car	Yes No Prefer not to say.
Reimbursement of commuting costs	Yes No Prefer not to say.
Access mode to public transport	Walking Cycling Car.

E.1.5. Attribute-based stated-choice blocks

After the background questions, respondents are introduced to the main stated-choice experiment. The introductory screen explains that the following questions concern their commute on days with temporary roadworks on their usual route to work. Respondents are asked to imagine a situation in which they normally commute by car and that, without roadworks, the one-way car trip takes approximately 35 minutes. On days with temporary roadworks, travel times and travel costs for three options change:

- continuing to travel by car;
- travelling by public transport;
- working from home.

For each SC task, a short text describes the moment of the roadworks morning, evening or both and the expectations regarding working from home on that day (fully possible, possible but with a preference for being at the office, or strongly discouraged because key tasks must be performed on site). Below the text, respondents see a visual table with three columns, one for each alternative. In each column, an icon represents the mode and the associated travel time and out-of-pocket travel costs are shown for that scenario. Respondents choose their preferred option by clicking the button below the corresponding column.

The attribute-based experiment consists of two blocks of six choice tasks each (SC block 1 and SC block 2), so that each respondent answers six attribute-based choice tasks in total. A block randomiser in Qualtrics ensures that the order of the two blocks is randomised at the respondent level and that the order of the tasks within each block is also randomised. This reduces potential ordering effects.

E.1.6. Pivoted stated-choice questions

In addition to the attribute-based blocks, car commuters receive three pivoted SC questions. These are only shown to respondents who reported the car as their usual primary commuting mode. The pivoted questions explicitly reference the respondent's own reported baseline travel time from Section E.1.4.

Before each pivot question, the text reminds respondents of their usual travel time and describes a temporary increase due to roadworks on their route. The three scenarios correspond to approximately 25%, 45% and 60% longer car travel times than usual. The alternatives (car, public transport, working from home) and the visual presentation are kept identical to those in the attribute-based blocks to maintain consistency. These pivoted tasks provide additional observations on how commuters respond

Normaal duurt uw autorit naar het werk ongeveer **35 minuten**.
Er zijn tijdelijke wegwerkzaamheden op uw vaste route naar het werk.
Deze zorgen vandaag **tijdens de avondspits (terugreis)** voor extra vertraging.
Op deze dag heeft u meerdere afspraken; fysiek aanwezig zijn heeft de voorkeur, maar **online deelnemen is mogelijk**.
In het overzicht hieronder ziet u voor deze dag de reistijd en reiskosten van de drie mogelijkheden.
De genoemde reistijden en reiskosten hebben betrekking op één enkele reis (heen óf terug), afhankelijk van het moment waarop de wegwerkzaamheden plaatsvinden.
Welke optie zou u in deze situatie het meest waarschijnlijk kiezen?

	Auto	Openbaar vervoer	Thuiswerken
Reistijd	70 minuten	50 minuten	
Reiskosten	€11	€12	

Auto ○ Openbaar vervoer ○ Thuiswerken ○

Figure E.2: SC question

to relative increases in their own door-to-door travel time.

E.1.7. Revealed-preference questions on previous roadworks

The RP module is also restricted to car commuters, since it concerns experiences with road closures or major roadworks on or near the usual car route to work. Respondents are first asked whether they have experienced such hindrance in recent years (yes/no). Those who answer “yes” receive two follow-up questions:

- Their typical response to these roadworks on commuting days, with three options:
  - Continuing by car with extra travel time
  - Switching to public transport
  - Working from home
- Open question in which they can briefly describe what kind of works were involved and where they approximately took place.

These RP questions serve as a qualitative cross-check on the plausibility of the SC responses and provide additional insight into how commuters actually respond to temporary road closures in practice.

F

Construction and justification of reference populations

This appendix documents the construction of the reference percentages used to benchmark the study sample against the Dutch adult population and the Dutch road-active population. Table F.1 reports the distributions for gender, age, education, driving licence status, Randstad residence, and workdays per week.

F.1. Dutch population

The column *NL Population (%)* represents the distribution in the Dutch population aged 18 and over. These figures were taken from official statistics of Statistics Netherlands (CBS) and from CBS/OCW sources on the highest attained educational level. Categories were aligned to the survey's classification.

For gender, the baseline distribution is obtained from CBS population statistics, which are primarily based on binary administrative registration (male/female). Any non-binary or non-response categories are either not available in standard administrative tables or are reported only in dedicated survey-based outputs; where needed for comparability, such residual shares were grouped into a single Other/Prefer not to say category (Centraal Bureau voor de Statistiek, 2024b, 2024c).

Driving-licence ownership for the general population is based on CBS publications and visualisations on driving licences (Centraal Bureau voor de Statistiek, 2024a, 2024g). The Randstad indicator is defined as residence in one of the Randstad provinces (Noord-Holland, Zuid-Holland, Utrecht, Flevoland), consistent with common regional delineations in Dutch mobility reporting (Kennisinstituut voor Mobiliteitsbeleid (KiM), 2024).

F.1.1. Road-active population: definition, source, and construction steps

The column *Road-active population (%)* does not represent the full population, but an *active subpopulation*: individuals who, on an average day, participate in road-based travel. The primary source is the CBS mobility survey Onderweg in Nederland (ODiN). ODiN is a large-scale, weighted travel survey designed to be representative of the Dutch population aged 6 and over after weighting by person characteristics (Centraal Bureau voor de Statistiek, 2024e, 2024f). For consistency with the study sample, the reference was restricted to ages 18+.

Choice of reference year (ODiN 2023).

ODiN 2023 was used as the primary benchmark for structural comparisons. ODiN 2024 introduced a methodological break and classification changes (including changes in background variables), which makes 2023 the more stable basis for benchmarking (Centraal Bureau voor de Statistiek, 2024d).

Operationalising “on the road”.
The road-active population was operationalised as persons who make at least one road-based trip on a typical day in ODiN. Importantly, this includes both drivers and passengers. As a consequence, a small share of the road-active population may not hold a driving licence, because they can still participate as car passengers. This is consistent with CBS mobility accounts where passenger kilometres constitute a non-negligible component of total car travel (Centraal Bureau voor de Statistiek, 2024f).

Deriving distributions by personal characteristics.
For each characteristic, the distribution was computed within the road-active population using ODiN’s person-level weights. In practice, this means selecting the relevant active population under the definition above, applying the CBS weights to obtain population-representative shares, and tabulating weighted proportions for the harmonised categories (Centraal Bureau voor de Statistiek, 2024e).

Education shares were taken from ODiN 2023 summary/appendix tables, where the highest attained education is reported in a format that can be aligned to the survey’s education categories (Centraal Bureau voor de Statistiek, 2024d).

Workdays per week (general population vs. road-active commuting exposure).
For workdays per week in the general workforce, the distribution is based on CBS labour market statistics from the Enquête Beroepsbevolking (EBB) (Centraal Bureau voor de Statistiek, 2024h). For the road-active population, workdays are interpreted as commuting exposure; individuals with more workdays generate more commuting occasions and are therefore expected to be overrepresented when focusing on the active commuting population. Conceptually, this can be implemented by conditioning on commuting participants and using an exposure-weighted distribution that scales person weights by the number of workdays before normalisation. This aligns the benchmark with the purpose of the comparison: describing the population *effectively present* on the road due to recurring commuting obligations.

F.1.2. Category harmonisation

Because official sources use different category schemes, categories were harmonised to enable a direct comparison with the study sample:

- **Gender:** the sample categories *Other* and *Prefer not to say* were combined into *Other/Prefer not to say*. Where non-binary or non-response categories are available in reference sources, these were also consolidated into a residual category; otherwise, administrative statistics remain largely binary (Centraal Bureau voor de Statistiek, 2024b, 2024c).
- **Education:** lower education categories were consolidated into *Secondary/Primary/None* if the source did not provide a directly matching breakdown. For ODiN 2023, comparable categories were taken from the published summary tables (Centraal Bureau voor de Statistiek, 2024d).
- **Age:** age bands were aligned to the survey (18–24, 25–34, 35–44, 45–54, 55–64, 65+).

F.1.3. Uncertainty and interpretation

When interpreting deviations between the study sample and the reference populations, it should be recognised that ODiN estimates for small subgroups (, *Other* gender or *no formal education*) may have relatively larger uncertainty. Moreover, the road-active population varies by day type and season. The road-active percentages used in this thesis are interpreted as an annualised “average day” benchmark to facilitate a meaningful comparison with population shares (Centraal Bureau voor de Statistiek, 2024f).

Table F.1: Comparison of the study sample with the Dutch population and the road-active population.

Category	Sample (%)	NL Population (%)	Road-active (%)
Gender: Male	59.8	49.2	56.4
Gender: Female	31.7	50.2	41.2
Gender: Other/Prefer not to say	8.4	0.6	2.4
Age: 18–24	15.3	10.2	8.4
Age: 25–34	45.5	16.3	21.2
Age: 35–44	19.0	15.4	20.8
Age: 45–54	9.0	15.1	19.5
Age: 55–64	10.6	17.0	18.2
Age: 65+	0.5	26.0	11.9
Education: WO Master or higher	45.0	14.7	18.2
Education: HBO	26.5	15.9	22.5
Education: WO Bachelor	13.8	6.5	8.4
Education: MBO	9.5	36.7	34.1
Education: Secondary/Primary/None	4.3	26.2	16.8
Driving licence: Yes	77.8	83.2	96.5
Driving licence: No	22.2	16.8	3.5
Randstad: Yes	60.8	51.0	44.5
Randstad: No	39.2	49.0	55.5
Workdays: 5	59.8	48.5	58.2
Workdays: 4	27.5	19.1	24.1
Workdays: 3	5.8	14.8	10.2
Workdays: 2	5.3	8.0	4.5
Workdays: 1	1.6	9.6	3.0

G

SC MNL specification search and benchmark selection

G.1. Model selection

This appendix documents the structured development of the benchmark SC MNL specification. Starting from the design-consistent model (SC_MNL_Start), a limited set of targeted extensions is estimated to test three substantive questions: (i) whether PEAK contributes incremental explanatory power, (ii) whether WFH feasibility must be modelled explicitly to avoid confounding preferences with constraints, and (iii) whether observed heterogeneity is sufficiently strong to motivate subsequent Mixed Logit and Latent Class modelling (Hensher et al., 2005; Train, 2008).

Across all candidate models, the selection principle is parsimony: additional parameters are retained only if they are behaviourally interpretable and improve penalised fit (AIC/BIC), rather than improving log-likelihood alone at the expense of model interpretability.

Table G.1: Candidate panel MNL specifications for the SC experiment. Lower AIC/BIC indicates preferred fit after penalising model complexity.

Model specification	k	Final LL	AIC	BIC
SC_MNL_Start (SC attributes incl. PEAK in WFH)	9	-901.19	1820.39	1849.12
SC_BASE (PEAK removed)	7	-901.84	1817.68	1840.03
SC_BASE + WFH feasibility	8	-877.65	1771.30	1796.84
SC_BASE + Randstad shift in PT	8	-901.75	1819.50	1845.04
SC_BASE + WFH feasibility + Randstad shift in PT	9	-877.57	1773.15	1801.88
SC_BASE + Observed Heterogeneity	22	-829.34	1702.68	1772.92

Table G.1 yields three results that guide the benchmark choice used in the main text.

Removal of PEAK

Although peak context was presented in the SC tasks, including PEAK does not improve penalised fit. The AIC and BIC of the design-consistent SC_MNL_Start are worse than those of the otherwise identical specification without PEAK (SC_BASE). This indicates that PEAK does not provide incremental explanatory power beyond time, cost, and on-site constraints in the current SC dataset. Consequently, PEAK is not retained and SC_BASE is used as the base specification for the remaining candidate models.

Modelling WFH feasibility

Adding WFH feasibility to SC_BASE produces a large improvement in fit (Final LL improves from -901.84 to -877.65; AIC and BIC decrease strongly). The magnitude of this improvement implies that feasibility captures a systematic component of WFH choice that is not represented by the SC attributes alone. Because feasibility has a clear structural interpretation and improves penalised fit, SC_BASE + WFH feasibility is adopted as the benchmark MNL in the main text.

Context and socio-demographic extensions

The Randstad shift does not improve fit relative to SC_BASE and does not improve the feasibility benchmark, and is therefore not retained in the benchmark specification. In contrast, the comprehensive observed heterogeneity model (SC_BASE + Observed Heterogeneity) provides the best statistical fit. This confirms that significant observed heterogeneity exists in the sample; however, this specification is not selected as the benchmark. The purpose of the MNL benchmark is to establish average population sensitivities in a parsimonious and interpretable way. The strong performance of the observed heterogeneity model therefore serves as a diagnostic motivation for the subsequent Mixed Logit and Latent Class models, which handle heterogeneity more systematically.

H

Mixed Logit specification search and benchmark selection

This appendix documents the specification search used to determine the structure of unobserved heterogeneity in the SC model. Five candidate Mixed Logit specifications were estimated to assess whether randomness is present in car travel time sensitivity, car cost sensitivity, and baseline WFH preference. All models were estimated using 1,000 Halton draws.

Car travel time sensitivity is a fundamental concept in transport economics. Commuters differ in time sensitivity due to scheduling constraints, comfort preferences, or the ability to multitask (Hess et al., 2005; Small, 2012). Capturing this heterogeneity reduces the risk of forecasting bias implied by imposing a single trade-off ratio on the full sample.

Similarly, sensitivity to car cost may vary due to differences in income and budget constraints. In the full search, a negative log-normal distribution was tested to ensure behavioural consistency (negative cost sensitivity) while allowing for scale differences across individuals.

Finally, baseline WFH preference may differ beyond objective constraints (feasibility and on-site obligations). Randomising the alternative-specific constant for WFH captures this unobserved "WFH perception".

Table H.1 summarises the model comparison results. Introducing heterogeneity substantially improves penalised fit relative to the fixed-parameter MNL benchmark.

Table H.1: Comparison of Mixed Logit specifications. All models were estimated using 1,000 Halton draws.

Model Specification	Random Parameters	LL	AIC	BIC
MNL Benchmark	None	-877.65	1771.31	1796.85
MXL 1	Time	-791.29	1600.57	1629.31
MXL 2	Cost	-791.20	1600.40	1629.14
MXL 3	WFH	-833.68	1685.36	1714.10
MXL 4	**Time + WFH**	**-747.86**	**1515.71**	**1547.64**
MXL 5	Time + Cost + WFH	-743.09	1508.18	1543.30

While the most comprehensive specification (MXL 5) achieves the lowest BIC, MXL 4 (Time + WFH) is selected as the preferred benchmark for theoretical interpretability in the context of this thesis. The primary objective of the subsequent Latent Class analysis is to identify segments related to *scheduling flexibility*. Allowing cost to be random risks conflating time-pressure heterogeneity with income-related heterogeneity (ability-to-pay effects). By selecting MXL 4, the benchmark isolates heterogeneity in time sensitivity and baseline WFH preference, which are the central behavioural constructs required for the segmentation analysis.

I

Latent Class model selection and specification testing

This appendix documents the selection of the Latent Class (LC) specification used in the main text. The selection involved two steps: choosing the number of classes (K), and determining which parameters are allowed to vary across classes.

Table I.1 summarises the candidate models and their fit.

Table I.1: Model selection for the Latent Class analysis.

Model Specification	Classes	Covariates	LL	BIC
LC3 (Constants only)	3	No	-762.62	1597.95
LC3 (With Covariates)	3	Yes	-741.49	1576.46
LC2 (Extended Parameters)	2	Yes	-785.72	1649.34
LC2 (Parsimonious)	**2**	**Yes**	**-785.71**	**1644.11**

Rejection of the 3-class structure

Statistically, the three-class solution yields a lower BIC. However, when extending LC3 to include covariates for profiling, the resulting model exhibits signs of overfitting and theoretical inconsistency. In particular, one class is estimated with a positive car travel time coefficient ($\beta_{\text{Time,Car}} = +0.15; p = 0.85$), implying utility from delay, which is inconsistent with behavioural theory. Moreover, the membership parameters associated with the third class are not statistically significant, indicating that the data do not support a stable third profile based on the available covariates. For these reasons, the three-class specification is not retained.

Specification of class heterogeneity

Within the two-class framework, the preferred specification restricts heterogeneity to the two dimensions that were identified as substantively and statistically important in the MXL benchmark (MXL 4): car time sensitivity and baseline WFH preference. Since cost heterogeneity was excluded in the MXL benchmark to preserve interpretability, the cost parameter is kept generic in the LC specification as well. This parsimonious LC2 specification provides the best trade-off between robustness and interpretability, and is therefore used as the benchmark in the main text.

J

Pivot model specification testing and selection

This appendix documents the stepwise specification search for the Pivot model. The model selection process was guided by two objectives: capturing the non-linear response to delay (inertia) and identifying the correct structural constraints on WFH.

J.1. Functional Form and Inertia

The pivot data show pronounced nonlinearity in switching behaviour, motivating comparisons among linear, log-linear, and percentage-based time specifications. As shown in the main text, standard time-based utility functions failed to capture the extreme stickiness of car choice at low disruption levels.

To address this, a ”Tolerance” indicator (D_{LowDelay}) was introduced for the 25% disruption scenario. This extension allows the model to separate baseline inertia from marginal time sensitivity.

J.2. Testing WFH Constraints

Beyond time sensitivity, the analysis tested which type of constraint best explains the resistance to working from home. Two hypotheses were compared:

1. **Flexibility Hypothesis:** Respondents with flexible working hours are more able to adapt (tested via an interaction with ‘Flexible_werkuur‘).
2. **Location Hypothesis:** Respondents with tasks requiring physical presence are structurally prevented from adapting (tested via ‘Werk_oplocatie‘).

Table J.1 summarises the stepwise improvement in model fit.

Table J.1: Stepwise comparison of Pivot specifications. The final model (Location Constraint) provides a vastly superior fit compared to models based solely on time or flexibility.

Model Specification	Parameters (k)	Log-Likelihood	AIC	BIC
1. Baseline Models				
Linear Time (Δt)	5	-192.17	394.34	406.30
Log-Linear Time ($\log(1+\Delta t)$)	5	-186.42	382.84	394.81
2. Inertia Extension				
Log-Linear + Tolerance	6	-177.13	366.26	380.63
3. Constraint Testing				
+ Tolerance + Job Flexibility	7	-173.56	361.13	377.89
+ Tolerance + Location (Final)	**7**	**-164.19**	**344.37**	**363.53**

J.3. Selection of the Preferred Specification

The comparison yields three key insights:

1. **Inertia is critical:** Adding the Tolerance parameter (Model 2 vs. Model 1) yields a substantial improvement (ΔAIC ≈ -16), confirming the existence of a threshold effect at 25% delay.
2. **Location dominates Flexibility:** While adding job flexibility (Model 3) improves the fit slightly compared to the tolerance-only model, the inclusion of the physical location constraint (Model 4) leads to a massive improvement (ΔAIC ≈ -17 compared to the flexibility model).

The Location Constraint model (Model 4) is statistically superior because it identifies a hard constraint: respondents who *must* work on location are effectively captive, whereas flexibility is a softer factor. Therefore, the specification with Log-Linear Time, Tolerance, and Location Constraints is retained as the preferred model.

K

Practical translation for Sweco

Working document based on the pivot results and profile analysis

Purpose: This document translates the academic findings into more directly usable guidance for project work, client discussions, and scenario development.

Key message

- A uniform 20% assumption is uncertain as a standard rule for roadworks.
- The behavioural response is non-linear: at low levels of disruption, almost everyone continues to drive, but at medium and high levels of disruption, the reduction in road traffic increases sharply.
- The direction of adaptation differs: under severe disruption, some shift to working from home and some to public transport; this depends on both profile characteristics and absolute additional travel time in minutes.

1. What do the data show directly?

The data are based on the pivot module, which uses car commuters and three levels of additional travel time: 25%, 45%, and 60%. The results show a clear turning point. At 25% additional travel time, 92.6% still remain in the car. At 45%, this falls to 53.1%, and at 60%, to 29.6%.

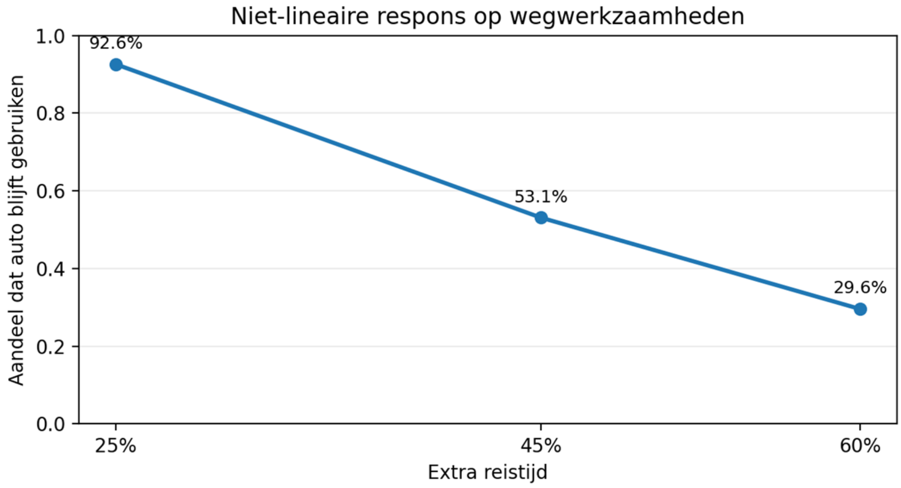


Figure K.1: Share continuing to use the car by level of additional travel time.

Table K.1 conveys the same message in compact form and also translates the percentages into average additional minutes.

Table K.1: Aggregate pivot results by severity level.

Severity	Additional travel time	Avg. extra min	Remain in car	PT	Work from home	Reduction on the road
Low	25%	10.9	92.6%	0.0%	7.4%	7.4%
Medium	45%	19.6	53.1%	17.3%	29.6%	46.9%
High	60%	26.2	29.6%	22.2%	48.1%	70.4%

2. Where does the adaptation go?

The reduction on the road should not be treated as a black box. Under low disruption, diversion is limited. Under medium disruption, both working from home and public transport increase. Under high disruption, working from home becomes dominant in the overall sample, while public transport also increases but remains secondary.

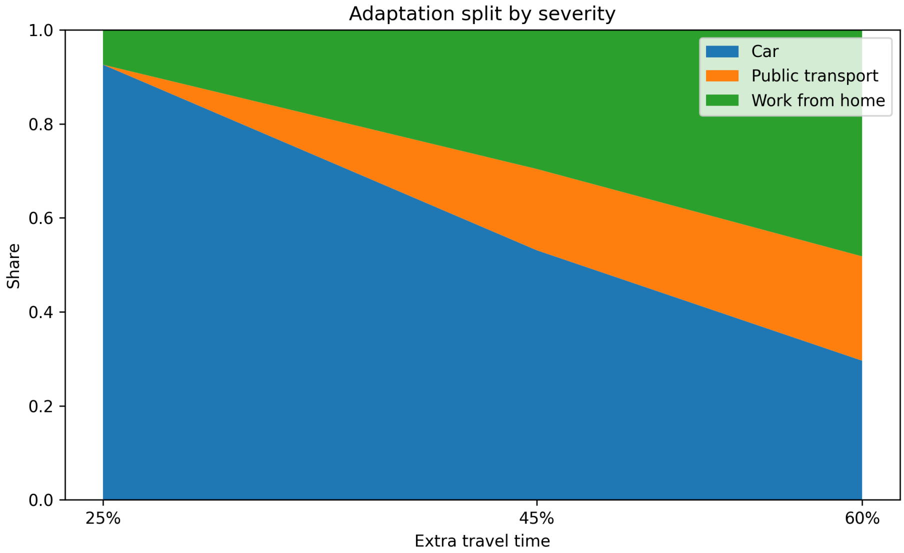


Figure K.2: Distribution of the response across car, public transport, and working from home.

3. Practical translation for Sweco

For Sweco, the first step is not to choose a single percentage, but to determine the severity of the disruption. After that, a bandwidth can be selected per project for the remaining road traffic and for the distribution between working from home and public transport.

Table K.2: Practical translation from severity to project application.

Severity	Practical interpretation	Indicative extra minutes	Indicative reduction on the road	Dominant response	Application
Low	Limited but noticeable disruption	around +10 min	approx. 5–10%	most people continue driving	do not automatically apply 20%
Medium	clear transition zone	around +20 min	approx. 40–50%	mix of working from home and PT	build scenarios, not one point estimate
High	strong disruption / severe impact	approx. +25 to +30 min	approx. 65–75%	strong adaptation pressure; working from home often substantial	use a separate high-impact variant

4. Further insight from profile differences

Profile differences are relevant, but they should always be interpreted together with absolute delay in minutes. In this sample, the group with high work-from-home potential has, on average, shorter commuting trips. The same percentage disruption therefore results in fewer additional minutes for this group. As a result, a profile graph does not reflect a pure work-from-home effect, but a combination of profile and exposure to additional travel time.

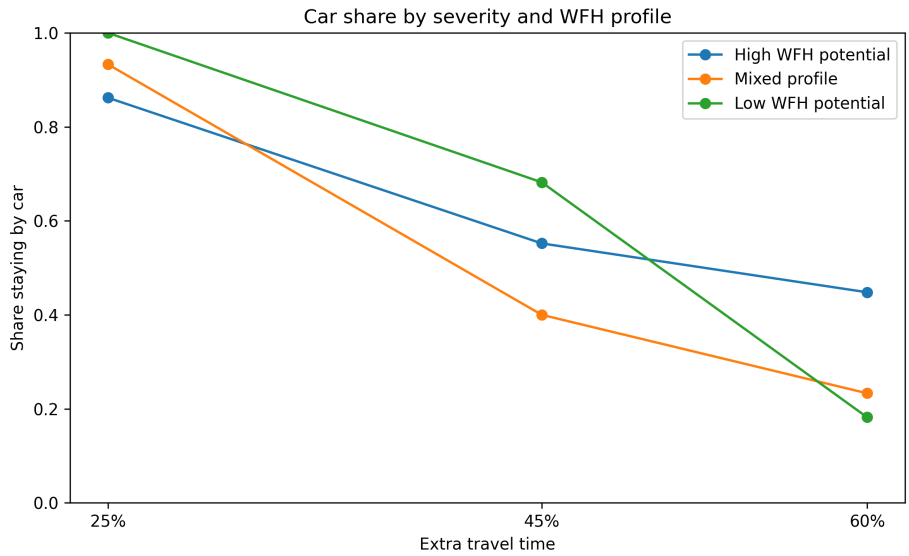


Figure K.3: Profile differences should be interpreted together with the average additional minutes of travel time.

Table K.3: Profile differences under high disruption (45% and 60% additional travel time).

Profile	Avg trip	High disruption: car	High disruption: PT	High disruption: WFH
Low work-from-home potential	45.5 min	18.2%	72.7%	9.1%
Mixed profile	48.2 min	23.3%	3.3%	73.3%
High work-from-home potential	37.5 min	44.8%	3.4%	51.7%

Interpretation for Sweco: under severe disruption, adaptation in the low work-from-home potential group shifts mainly towards public transport; the mixed profile is the strongest transition group towards working from home; the high work-from-home profile also shows more working from home, but in this sample faces fewer additional minutes on average.

5. Reality check: stated versus realised behaviour

The pivot results show how behavioural pressure increases as disruption intensifies. However, the revealed-preference module in the thesis shows that realised behaviour in practice is more conservative. Among car commuters who reported having previously experienced major disruption, the car remained dominant more often than the stated-choice results alone would suggest. This points to an intention–behaviour gap: in reality, habitual behaviour, uncertainty, information, practical frictions, and transaction costs play a stronger role.

Table K.4: Comparison between pivot scenarios and RP outcomes under disruption.

Source	Car	PT	Work from home	Practical interpretation
Pivot – medium disruption (45%)	51.3%	17.3%	29.6%	Scenario with controlled severity; shows the direction of adaptation.
Pivot – high disruption (60%)	29.6%	22.2%	48.1%	Scenario with controlled severity; shows the direction of adaptation.
RP – experienced major disruption	75.9%	5.6%	18.5%	Real-world check; shows much stronger car persistence.

For Sweco, this means that the severity profiles are particularly strong as scenario and directional information. They should not be used as direct point estimates for realised switching rates. The pivot should therefore be read as an indication of the behavioural structure and the upper bound of adaptation pressure, while the RP module indicates that actual switching in practice is likely to be more moderate.

6. Recommendations for Sweco

- Do not replace the fixed 20% assumption with one new percentage, but with severity-dependent bandwidths. This ensures that the percentage is better aligned with the situation.
- Use profile information as a refinement. Where possible, consider per corridor or project the distribution on the road in relation to the extent of location-bound work, flexibility, and work-from-home potential.
- In projects, work with at least three variants: conservative, central, and high adaptation. This makes uncertainty more visible than using a single fixed input value.

Important nuance
This note is intended as a practical translation for project work and client discussions. The bandwidths are derived from the analysed sample and should therefore be interpreted as scenario input and decision support, not as directly nationally calibratable truths.