Understanding the Drivers of Sick-leave Behaviour

Dutch Sick-Leave Incentives in Comparative Perspective

Comparative Evidence from a Multinational Logistics Company

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Emile Wesselink

Student ID: 5156386

Supervisors: Maarten Kroesen, Nikos Pachos-Fokialis

Picnic B.V.

MSc Engineering & Policy Analysis

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Abstract

Sickness absence is an increasingly important operational and policy concern in the Netherlands, particularly in the context of labour shortages, demographic ageing, and pressure on workforce availability. However, registered sickness absence does not reflect illness alone. From an absence-threshold perspective health complaints, fatigue and private circumstances lead to reported absence only when they cross a threshold shaped by institutional incentives, employment conditions and individual circumstances. This thesis asks: To what extent are national social security frameworks, individual factors, including worker profile and job context, and exogenous factors associated with sickness absence behaviour of logistics workers in the Netherlands, Germany, and France?

The study applies a within-firm, cross-country comparative design using Picnic's frontline operations, allowing different national sick-leave regimes to be examined while keeping the employer and broad work context relatively comparable. Data covers warehousworkers and delivery drivers in employee-week observations from 2024–2025. A structured institutional policy analysis is combined with analysis of a novel individual-level set of employee-, operational- and contextual variables to explain sickness absence patterns. Exploratory analyzes compare spell-duration distributions with national arrangements concerning waiting days, medical certification, wage replacement, and employer obligations. Ordinary least squares models analyze weekly sickness absence rates, supported by robustness models, while Cox proportional hazards models examine sickness-spell duration.

The findings show that sickness absence is multidimensional, with different determinants shaping different absence margins. In the Netherlands, frequent one-day absence is consistent with a relatively low reporting threshold resulting from the absence of mandatory medical certification and the conditional use of waiting days. Shopper timing patterns and cold-zone exposure further suggest that some short-term absence may be discretionary or operationally avoidable. By contrast, the Dutch long-term burden may reflect the interaction of prolonged employer wage continuation with an older, longer-tenured workforce and the positive association between permanent contracts and absence. In Germany, day-one certification appears to limit the shortest spells, while the absence of waiting days and full wage replacement during the first six weeks are consistent with higher short- and medium-term absence. German absence is also strongly associated with local operational conditions, including staffing, Captain absence, lateness, performance, and disruptions. France combines waiting days and day-one certification with the lowest absence frequency, while its negative tenure patterns suggest that absence may be more closely related to workforce retention than to long-duration benefit incentives.

Across countries, the most relevant non-policy determinants concern employee profile, scheduling, team context, and external shocks. Age is most clearly associated with long-term absence, while gender is the most consistent correlate of higher absence rates, although this likely reflects legitimate recovery rather than operationally avoidable absence. Tenure and contract type are more context-dependent and appear to capture workforce selection, retention, and employment attachment. Recurring operational findings include recent scheduling intensity among Shoppers, Chilled and Frozen shift exposure, and local Captain context and disruption sensitivity among Runners. Overall, national policy alone does not explain sickness absence; rather, policy interacts with workforce and operational conditions, creating actionable opportunities to improve reliable attendance and productivity.

These findings imply that sickness absence should not be addressed as one uniform problem. The cross-country patterns suggest that Dutch high short-term absence and persistent cases, through operational interactions, are related significantly to certification requirements, waiting days and financial incentives. This provides a strong argument for the Ministry of Social Affairs and Employment to their ability of mitigating these margins through the respective levers, after assessment of the true recovery need of this population. Operationally, logistics' should monitor absence short- and long-term absence separately through an aggregate dashboard across roles and countries, as results show distinctly different relationships per margin. Operational priorities include preventing timing- and cold-zone-related short absence and strengthening long-term reintegration in the Netherlands, improving local performance-, and disruption management in Germany, and supporting job fit, and talent retention among French Shoppers.

The results are associative rather than causal and are based on registered sickness absence within one company. The data do not directly measure health, private circumstances or presenteeism, while employee selection into contracts, shifts, teams, and locations may influence the estimated associations. The cross-country findings should therefore not be interpreted as pure national policy effects or automatically generalised beyond comparable frontline logistics settings. Future research should combine administrative data with employee or occupational-health information and evaluate policy changes or operational interventions through quasi-experimental designs or phased field trials.

Contents

1 Research Problem & Objective

1.1 Introduction

In today's labour market, the Netherlands faces structural challenges with no quick resolution. Across Europe, persistent labour shortages constrain output and make staffing increasingly difficult (CBS, 2025), while demographic ageing continues to put long-term pressure on social security systems and their sustainability (ISSA, 2024). Against this backdrop, sickness absenteeism has become an increasingly relevant productivity issue in the Netherlands. The societal costs are substantial: Recent CBS figures show sickness absence cost increasing with roughly €6 billion over the past five years (CBS, 2026; Inkomenscollectief, 2025). In 2024, sickness absence was estimated to be at a new high, 5% nationally (CBS, 2026). As a result, both the Ministry of Social Affairs and Employment and employers are searching for absence policies that support productivity without undermining worker health.

Sickness absenteeism is inherently difficult to steer: its causes are multifactorial, spanning health, professional and contextual conditions, and privacy regulations limit what firms can observe at the individual level. At the same time, absence is also a legitimate recovery mechanism that can not be scaled down completely. However, Kremer (2009) has shown that 21,5% of absence in The Netherlands was attributable to avoidable cases, so rising absence creates a central dilemma: which absence reflects necessary recovery versus avoidable behaviour that could be reduced without harming health. This is precisely why effective policy cannot rely on a single aggregate absence rate. It must understand where absence concentrates in the duration distribution (short-, or long spells) and for whom, because different margins imply different mechanisms and require different policy levers to steer it.

Sickness absence is especially acute in firms with large frontline workforces and high operational interdependence; There, it quickly translates into rescheduling, replacement costs, and immediate productivity losses (Kirkegaard et al., 2024). Consequently, in this sector, effective institutional absence policy, and how firms can operate within it, is crucial for productivity. This thesis focuses on Picnic, a fast-growing online grocery retailer operating under different national sick-leave regimes (Picnic, 2026), the Netherlands, Germany, and France, as a strategic setting to study sickness absenteeism as a system shaped by both institutional incentives and work context. While work processes are broadly comparable across countries, sickness absence levels differ substantially, and the extent to which this gap reflects institutional incentives, in-firm workforce, operational, or contextual differences is not yet clear.

However, these cross-country differences within a largely similar operational environment create a rare, like-for-like setting that enables us to assess whether observed sickness absence patterns are consistent with policy incentives or operational factors, and to identify where and with whom absence concentrates. Using Picnic's granular operational data, this thesis addresses an EPA-relevant policy issue by applying comparative institutional analysis and multivariate regression models to distinguish institutional patterns from external, work- and workforce-driven explanations. The study objective is to translate these diagnostics into an evidence-base for;

sickness absence policy of the Ministry of Social Affairs and Employment, and operationally feasible interventions for logistics focussed on absence within Dutch institutional constraints.

1.2 Knowledge gaps

This section introduces the main limitations in the existing sickness absence literature and uses them to motivate the knowledge gaps addressed in this thesis. A more comprehensive review of the relevant theoretical and empirical literature is provided in Chapter 2.

First, institutional studies such as Palme and Persson (2019) and Hall (2022) mainly compare national sickness absence rates or policy frameworks at an aggregate level. These studies provide valuable insight into how sickness absence systems differ between countries, but they are less able to account for differences in work environments, workforce composition and job characteristics. As a result, it remains difficult to determine whether observed cross-country differences in sickness absence are related to national policy frameworks themselves, or whether they partly reflect differences in the types of workers and jobs being compared.

Second, literature reviews on sickness absence determinants, such as Beemsterboer et al. (2009) and Čikeš et al. (2018), show that a wide range of individual, health-related and work-related factors have been studied. However, this evidence often has a limited scope and is fragmented across different sectors, countries and study designs. Moreover, existing studies have a limited collection of determinants in one model. This limits the extent to which the relative importance of different determinants can be assessed while controlling for other relevant factors.

This existing literature points to two connected gaps that are important for understanding sickness absence behaviour and for developing an evidence base for absence policy and operational interventions.

First, for the Netherlands specifically, research on how institutional sickness absence incentives relate to the absence distribution remains limited. The Netherlands is often included in aggregated cross-country comparisons, but these studies usually rely on broad absence indicators and do not provide detailed insight into how specific policy levers may be associated with absence frequency, absence duration, or return-to-work behaviour. As a result, there is limited evidence on whether Dutch institutional arrangements create effective incentives for reliable attendance and timely return-to-work. Reform-based causal studies from other countries provide stronger evidence on the effects of policy changes, but such settings are rare, context-dependent, and not available for the Dutch case in the period studied. The literature therefore lacks a setting in which sickness absence policy can be compared across regimes under broadly comparable work conditions.

Second, although many determinants of sickness absence have been studied, the literature still lacks analyses that combine a more complete set of individual-level and job-context drivers within one empirical framework. Previous studies often focus on standard demographic or employment characteristics, such as age, gender, tenure, contract type, or working hours, but have less access to granular operational variables. In particular, existing research has limited evidence on factors such as distance to the workplace, shift type, planned hours per week, performance, lateness, and team or leadership context. Including these variables is important because cross-country differences in sickness absence may otherwise be attributed to policy, while they may partly reflect differences in workforce composition, job structure, or operational conditions.

Taken together, the scientific limitation of literature is therefore not simply a lack of studies, but a lack of integration. This thesis addresses these gaps through a novel like-for-like comparative design within one firm across the Netherlands, Germany, and France. By analysing comparable frontline logistics work across different national sickness absence regimes, the study reduces confounding from employer and broad job design, while still allowing institutional differences to be examined. The thesis combines exploratory policy and absence-pattern analysis with regression models of sickness absence rate and sickness spell duration. Rather than making causal claims, it provides an integrated system-level understanding of how national social security frameworks, worker-profile characteristics, job and operational context, and exogenous factors are associated with sickness absence behaviour. In doing so, it strengthens comparative sickness absence research and provides an evidence basis that can be translated into actionable strategies for firms and policy reflection for government.

1.3 Research Questions

This thesis investigates sickness absence behaviour among logistics workers in the Netherlands, Germany, and France using a within-firm comparative research design. The analysis combines institutional comparison, exploratory absence-pattern analysis, and regression-based analysis of individual-level absence data. National sickness absence frameworks are used to contextualise cross-country differences in observed absence behaviour, while the regression models examine how worker-profile characteristics, job and operational context, and exogenous factors are associated with weekly sickness absence rates and sickness spell duration. By combining these elements from three countries, the thesis assesses which absence patterns appear related to institutional context, which are more closely associated with workforce or operational characteristics, and which findings are most relevant for organisational action and Dutch policy reflection. To answer the research question:

To what extent are i) national social security frameworks, ii) individual factors (employee characteristics, operational context) and exogenous factors associated with sickness absence behavior of logistics workers in the Netherlands, Germany, and France?

SQ 1: Policy incentives mapping

How do national social security frameworks differ across the Netherlands, Germany and France and to what extent are they associated with observed absenteeism?

This sub-question maps key institutional levers and benchmarks them against observed absence burdens in broadly similar logistics operations across the Netherlands, Germany, and France. It compares absence frequency and duration distributions and overlays these patterns on the relevant regime differences to assess whether cross-country outcomes are broadly consistent or whether deviations concentrate in at policy margins where avoidable absence is plausible. The purpose of SQ1 is therefore to identify which aspects of national sickness absence regimes appear aligned with reliable attendance and timely return-to-work, and which policy elements may be more vulnerable to incentive-sensitive responses.

SQ2: Regression-Based Analysis of Sickness Absence Drivers

To what extent are sickness absence rates and sickness spell duration associated with employee characteristics, operational context and exogenous factors across the Netherlands, Germany, and France?

This sub-question provides the empirical diagnosis of sickness absence in logistics' frontline workforce. Supported by an investigative explorative analysis, it examines where sickness absence is concentrated, how this differs between the Netherlands, Germany, and France, and whether higher or lower absence is associated with differences in employees, work context, operational conditions, external shocks. By considering both weekly sickness absence rates and sickness spell duration, SQ2 distinguishes between the overall burden of absence and the persistence of absence once a sickness spell has started. This is important because the same absence rate may reflect different underlying patterns, such as many short spells, fewer long spells, or a combination of both.

The sub-question examines sickness absence from three complementary perspectives. Employee characteristics help assess whether absence differences are related to who works in each country or role. Operational context help assess whether absence is connected to how work is organised and experienced. Exogenous factors help separate internal workforce or operational patterns from broader shocks and disruptions.

The purpose of SQ2 is therefore to identify the main empirical patterns and associations that structure sickness absence across the three countries. It does not yet translate these findings into a basis for interventions or policy recommendations, but establishes which types of factors appear relevant for understanding differences in sickness absence rates and spell duration.

SQ 3: Actionable organizational and institutional evidence-base

(i) Which actionable factors in logistics' operations are associated with sickness absence, and (ii) which aspects of national social security frameworks appear to shape sickness absence behaviour across the Netherlands, Germany, and France?

This sub-question translates the empirical findings into an evidence basis for both firm-level action and policy reflection. The first part identifies operational factors within general logistics' sphere of influence that are associated with sickness absence in the Netherlands, thereby indicating where practical interventions may be most feasible. The second part places these findings in a broader comparative perspective by considering which aspects of national social security frameworks appear to shape sickness absence behaviour.

Subsequently, a cross-country comparison is used to assess whether associations are mainly consistent or whether they differ systematically between national contexts. Consistent patterns across countries may indicate that absence behaviour is more strongly related to worker composition or operational conditions. Differences between countries may suggest that institutional context, local labour-market conditions, or country-specific operational structures shape absence behaviour. The results are interpreted as associative rather than causal.

Additionally, SQ3 also considers what type of absence the observed patterns may suggest. This includes legitimate recovery absence, operationally avoidable work-related absence, discretionary short-term absence, and incentive-sensitive margins such as moral hazard or presenteeism. These distinctions are important because different types of absence require different organisational and policy responses. Together, SQ3 connects the empirical analysis to actionable organisational responses within logistics and broader policy reflection on institutional incentives around sickness absence.

1.4 Overall Approach

This thesis applies a novel like-for-like comparative design within one firm across the Netherlands, Germany, and France. The study combines exploratory institutional and absence-pattern analysis with regression-based analysis of individual-level sickness absence data. The approach is interpretive rather than strictly causal: it aims to develop a system-level understanding of which factors are associated with sickness absence and how these associations differ across institutional and operational contexts.

The empirical scope is limited to Picnic's frontline operational workforce, with the main focus on Shoppers and Runners, as these are the largest and most comparable employee groups across countries. Captains are included only where relevant as part of the operational team context, while other Picnic employees fall outside the scope of the analysis. Temporary agency workers are also excluded due to data limitations, as they are not consistently observed in the linked administrative data. The research consists of three main analytical components, corresponding to the three sub-questions.

SQ1 maps institutional policy and observes national sickness absence patterns. In an emprical explorative format, the sub-question maps the sickness absence systems in the Netherlands, Germany, and France, with particular attention to sick-pay arrangements, waiting days, employer obligations, certification requirements, reintegration rules, spell-linking rules, and employee incentives. These institutional levers are then compared with observed absence patterns in the data, particularly absence rate, absence spell duration, and, where relevant, absence frequency. This provides the policy context needed to interpret cross-country differences and helps identify which institutional features appear most relevant for observed absence patterns.

SQ2 uses multivariate models to estimate how employee profile, job and operational context, and exogenous factors are associated with sickness absence. It starts with an explorative analyses of individual and operational determinants of sickness absence descriptively. This includes differences in worker profile, role, tenure, contract type, commuting distance, scheduling, performance, lateness, leadership or team context, and exogenous conditions such as influenza, economic growth, and major operational disruptions. This exploratory step is used to identify relevant absence margins and to provide context for the regression models necessary for validation and interpretation.

The analysis is structured around two main operational absence outcomes: absence rate and sickness spell duration. Absence rate is analysed using OLS regression on employee-week observations, where the dependent variable captures the share of expected working time lost to sickness absence in a given week. Because repeated weekly observations from the same employee may be correlated, an additional person-level aggregated OLS model is estimated as a robustness check. In this model, each employee appears once, and absence is measured as the total absence rate over the full observed period. Sickness spell duration is analysed using survival analysis, where the event is defined as the end of a sickness absence spell. This allows the analysis to distinguish factors associated with the overall absence burden from factors associated with the length of sickness spells.

SQ3 offers operational and policy strategy foundation, it focuses on interpreting the results by assessing whether observed absence patterns appear mainly country-dependent, logistics-dependent, or driven by broader external conditions. Cross-country differences are used to distinguish patterns that may be related to national policy design from patterns that recur across logistics operations and are therefore more operationally actionable. Particular attention is given to variables within logistics' sphere of influence, such as scheduling, shift allocation, staffing conditions, lateness, site-level differences, leadership context, and workload proxies. Where relevant, the interpretation also considers that the overall absence rate reflects both the frequency with which sickness spells occur and the duration of those spells. This helps distinguish whether a finding points more towards short-term absence occurrence, longer recovery and reintegration processes, or both. The interpretation also considers what type of absence the results may be suggestive of, such as legitimate recovery absence, avoidable work-related absence, discretionary absence, or moral-hazard-sensitive margins, without classifying individual cases directly. This cross-country analysis ultimately provides a basis for both logistics' operational response and policy reflection focussed for the Ministry of Social Affairs and Employment.

Pure cross-country benchmarking based on national absence rates is difficult to interpret because countries differ in sector composition, workforce characteristics, reporting norms, culture, and employer practices. Quasi-experimental reform designs can provide stronger causal identification, but require policy shocks or sharp institutional thresholds that are not available for the Dutch setting during the study period. A single-country firm study would allow detailed analysis of logistics-specific operational drivers, but would not show whether observed patterns are country-dependent or more generally present across logistics operations.

For this reason, the within-firm comparison across the Netherlands, Germany, and France provides a useful middle path. It improves comparability by holding the employer, business model, and broad frontline work context relatively constant, while still allowing differences between national regimes and local operations to be examined. The design therefore remains cautious about causal claims, but is well suited to identifying which absence patterns appear more closely related to national institutional context., which seem operationally actionable for logistics, and which are more likely shaped by broader external conditions.

1.5 Thesis structure

The introduction establishes sickness absence as both an operational productivity issue and a policy-relevant problem, especially in a context of labour shortages and cross-country differences in sick-leave institutions. The literature review then builds the theoretical foundation by identifying three necessary lenses: determinants of sickness absence, the conceptual model linking individual, operational, exogenous and policy factors, and the policy levers that may shape absence behaviour. In parallel, the absence-type framework clarifies that observed sickness absence should not be interpreted as illness alone, but as a layered outcome that may include legitimate recovery absence, avoidable work-related absence, and more discretionary or incentive-sensitive margins. This creates the logic for the empirical analysis: policy may shape absence thresholds and return-to-work behaviour, but workforce composition and operational context must also be analysed before drawing conclusions.

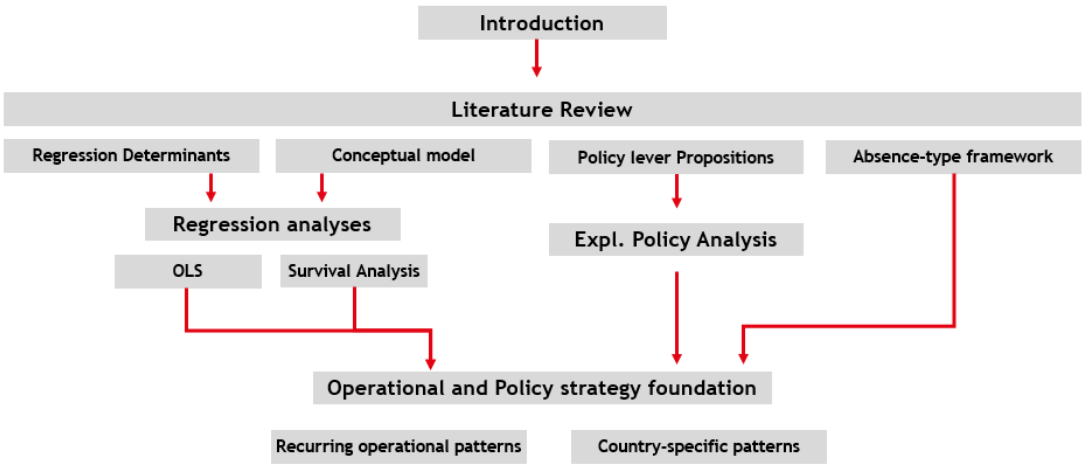

Figure 1: Thesis Structure

The empirical part then follows this logic in two connected streams. First, the exploratory policy analysis compares the Dutch, German and French sick-leave frameworks and assesses whether observed absence-frequency and duration patterns are consistent with propositions around waiting days, wage replacement and certification requirements. Second, the regression analyses test which worker-profile, job-context, operational and exogenous factors are associated with sickness absence rate and spell duration, using OLS for the overall absence burden and survival analysis for return-to-work dynamics. The final synthesis brings these streams together in the operational and policy strategy foundation: recurring patterns across countries are interpreted as more likely operationally actionable for general logistics, while country-specific patterns are used to reflect on how national institutional frameworks may shape absence behaviour. In this way, the thesis moves from theory to evidence and from evidence to practical and policy-relevant interpretation, without claiming direct causality where the design only supports associative conclusions.

2 Literature review

The literature search was structured around the analytical needs of this thesis rather than around the ambition to provide an exhaustive overview of all sickness-absence research. Its purpose was to identify the studies most relevant for four tasks: clarifying what sickness absence represents, determining how it should be measured, identifying which factors may explain variation in it, and integrating these insights into a conceptual model. Following this logic, the search first focused on literature that helped define the concept of sickness absence. This included studies distinguishing sickness absence from illness, introducing the concepts of legitimate recovery absence, avoidable absence, and discretionary absence, and positioning sickness absence in relation to presenteeism. Establishing this conceptual foundation was necessary to avoid treating observed absence as a simple proxy for health and to justify the broader behavioural perspective adopted in the thesis.

Second, the search targeted literature on the measurement of sickness absence, particularly studies clarifying the distinction between frequency, duration, and incidence, and assessing which of these indicators best matched the mechanisms studied in this thesis. Third, the search focused on literature explaining variation in sickness absence. At the institutional level, this meant studies on national sick-leave policy and social security frameworks, including international quasi-experimental evidence where Dutch reform evidence was limited. At the worker and workplace level, it meant identifying recurring employee-profile, role-specific, and job-context variables relevant for explaining within-firm variation. Finally, the search included literature on organisational and behavioural incentives, because these help interpret how institutional rules, company practices, and individual circumstances may jointly shape sickness absence behaviour. Together, these strands ensured that the literature review directly informed variable selection, interpretation, and the conceptual model used in this thesis.

Contentwise, this literature review approaches sickness absence as a multidimensional phenomenon rather than as a simple reflection of illness. It therefore begins by clarifying what sickness absence is conceptually, distinguishing between legitimate recovery absence and more avoidable or discretionary margins of absence behaviour, and positioning sickness absence in relation to related concepts such as presenteeism. It then turns to the question of measurement, since the literature shows that sickness absence can be operationalised in different ways, with measures such as frequency, duration, and incidence each capturing different mechanisms and dimensions of the phenomenon.

Against that conceptual and methodological background, the review next examines the main strands of the explanatory literature. First, it considers institutional determinants, focusing on how national sick-leave policy shapes the incentives, constraints, and trade-offs surrounding sickness absence. It then turns to individual and organisational determinants within the firm, distinguishing between employee profile characteristics and aspects of the immediate job context that may influence absence behaviour among otherwise comparable workers. Finally, it considers exogenous and contextual sources of variation, such as influenza peaks, holidays, weather, and broader calendar effects, because these may affect observed absence independently of policy or firm-level operations. Together, these strands provide the foundation for the empirical analysis by clarifying what sickness absence represents, how it can be measured, which factors may explain variation in it, and how these factors are brought together in the conceptual model of this thesis.

2.1 Sickness Absence

Sickness absence is not simply the same as illness. In the occupational-health literature, sickness absence generally refers to absence from paid work attributed to illness, injury, or reduced work capacity, usually within an institutional framework that grants income protection and legitimises temporary withdrawal from work (Alexanderson, 1998). At its core, the institution of sick leave exists to allow workers time to recover without immediately losing their livelihood, and therefore has both a medical and a social-protective function. At the same time, a long line of research stresses that sickness absence should not be treated as a direct or transparent measure of health status alone, because it also reflects administrative rules, workplace context, social norms, and behavioural choices. Alexanderson (1998) therefore describes sickness absence as a complex phenomenon shaped by multiple levels of determinants rather than as a simple indicator of disease, while Wikman et al. (2005) empirically show that illness, disease, and sickness absence capture related but distinct aspects of ill health.

To better capture drivers of sickness absence in this thesis, it is useful to distinguish analytically between legitimate recovery absence and an avoidable margin of sickness absence. Legitimate recovery absence refers to sickness absence that is primarily consistent with the core purpose of sick leave: providing time and rest for recovery when work participation is temporarily not sustainable or medically inadvisable (OECD, 2020). This category aligns most closely with the traditional medical understanding of sick leave as an instrument that protects health and income during genuine work incapacity. However, the literature also shows that observed sickness absence often contains an avoidable component, meaning that some absence may be preventable, or only partly driven by underlying medical necessity (Kremer, 2009). In that sense, sickness absence is better understood as the outcome of a process in which health complaints are filtered through institutional and behavioural conditions, rather than as the automatic consequence of illness itself (Allegro & Veerman, 1998).

This broader behavioural interpretation is captured well by the absence-threshold perspective associated with Allegro and Veerman (1998). In that view, workers do not respond mechanically to health complaints; rather, they cross a threshold at which reduced health, fatigue, strain, or private circumstances are translated into reported sickness absence. That threshold is shaped by incentives and constraints such as income replacement, ease of replacement at work, job security, certification rules, and workplace norms. A lower threshold means that a wider range of complaints or burdens may lead to sickness reporting, while a higher threshold means that workers may continue working despite comparable complaints. This perspective helps explain why sickness absence is often associated not only with health-related factors, but also with contract conditions, schedule characteristics, job satisfaction, and policy design.

Within this broader margin, the literature suggests a further distinction between avoidable absence that remains health-related and avoidable absence that is not primarily health-related. Kremer and Steenbeek's (2009) study of Dutch workers is especially useful here because it explicitly investigates avoidable sickness absence rather than inferring it indirectly. They estimate that about 21.5% of sickness absence can be considered avoidable, and they divide this share into a 10,5% health-driven avoidable component and a 11% non-health-driven avoidable component. The first category includes absence that originates in real health complaints but could in principle have been prevented through better working conditions, lower exposure, better scheduling, or other operational improvements. A work-related avoidable sickness absence. The second category refers more clearly to absence influenced by private reasons, behavioural discretion, or the incentive effects of institutional arrangements. This distinction is important because it shows that "avoidable" does not necessarily mean "fake" or "illegitimate"; part of avoidable sickness absence may still be linked to genuine health problems, but to health problems that were themselves preventable.

A narrower concept within the latter category of the avoidable margin is discretionary absence. In sickness-absence literature, this idea is often approached through the notion of short-term or uncertified absence, where the decision to report sick is less tightly determined by severe medical incapacity and may be more sensitive to individual judgement and organisational context (Tharenou, 1993). In practice, however, discretionary absence is difficult to observe directly, because administrative data record that a worker is absent due to sickness but do not reveal whether a specific spell was medically unavoidable, partly avoidable, or behaviourally timed; more generally, sickness absence is not a transparent indicator of health status alone (Alexanderson, 1998). The literature therefore tends to treat discretionary absence as a behavioural category that is inferred indirectly rather than measured cleanly at spell level.

One way this is done is by examining whether sickness absence responds to monitoring arrangements, calendar-based opportunities, or other non-health-related timing patterns. Boeri et al. (2021), for example, show that home visits during sick leave can reduce subsequent absence, suggesting that at least part of sickness absence is responsive to verification and deterrence. Böheim and Leoni (2020) similarly test whether sickness absence increases on bridging days that make it easier to extend leisure periods, thereby using calendar structure to identify a potentially incentive-sensitive component of short-term absence. Nicholson et al. (1978), in turn, show that absence patterns vary systematically by shift timing, day of the week, and position in the shift cycle, suggesting that the timing of sickness spells may also reflect situational and behavioural influences rather than health need alone. Together, these studies illustrate how the literature studies discretionary absence indirectly, through behavioural responses to context and timing rather than through direct observation of intent.

Beyond distinctions within sickness absence itself, the literature also distinguishes sickness absence from presenteeism. Presenteeism is not simply the opposite of absenteeism; rather, the two behaviours are related but distinct responses to impaired health under different organisational and incentive conditions (Johns, 2010). Research on presenteeism shows that workers often face a choice between staying home to recover and attending work while ill, and that this choice is shaped by constraints on absenteeism, job demands, attendance pressure, and replaceability (Miraglia

& Johns, 2016). In this sense, more generous sick-pay systems may increase sickness absence at one margin, called moral hazard, while reducing harmful presenteeism at another (Reuter & Gau, 2025). Conceptually, this matters because lower sickness absence is not automatically welfare-improving: it may reflect less avoidable absence, but it may also reflect workers attending work when recovery would have been preferable (Miraglia & Johns, 2016).

Taken together, the literature suggests that sickness absence should be understood as a layered concept, as shown in Figure 3. At one end lies legitimate recovery absence, which reflects the main protective function of sick leave. A smaller section of that consists of an avoidable health-related margin, where real sickness is present but might have been prevented through workplace or operational changes. Within that lies a non-health-related or more discretionary margin, where the reporting decision is more strongly shaped by incentives, norms, private circumstances, and institutional design. At the same time, sickness absence should be distinguished from presenteeism, since lower observed absence does not necessarily imply better health or welfare outcomes. This conceptualisation is useful for the present study because it provides a basis for understanding both what factors may influence sickness absence and how absence behaviour may be shaped through the interaction between health, policy incentives, organisational conditions, and individual circumstances.

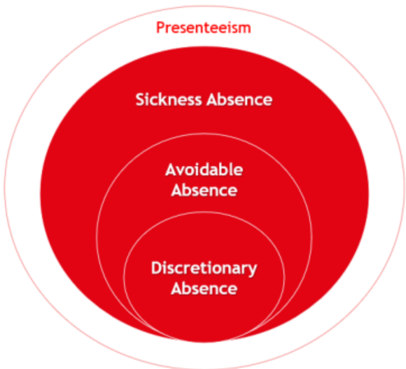

Figure 2: Absence-type Framework

2.2 Measuring sickness absence

A second issue in the literature is that “sickness absence” can be measured in several different ways, and these measures do not capture the same underlying phenomenon. Hensing (1998) remains a key reference here, arguing that the choice of indicator should follow the research question rather than being treated as interchangeable. She distinguishes five core measures: frequency of absence spells, length of individual spells, incidence rate, cumulative incidence, and duration of absence over a defined period. Later methodological work continues to use this distinction and similarly emphasises that sickness absence is multidimensional: some indicators capture how often workers report sick, others capture how long they remain absent once a spell begins, and still others capture the share of workers who become absent at all (M. Ravinskaya, et al., 2022).

The most common distinction in applied research is between absence frequency and absence duration (Beemsterboer et al., 2009), and this distinction is not only methodological but also substantively important. Frequency refers to the number of sickness absence episodes within a given period and is particularly relevant for understanding short-term and operational absence patterns (Bakker et al., 2003). Because frequent short spells are more likely to reflect day-to-day attendance behaviour, reporting thresholds, and discretionary margins of absence, frequency measures are especially useful when the interest lies in short-term workforce availability and the behavioural responsiveness of employees to workplace or institutional incentives (Hensing, 1998; Beemsterboer et al., 2009).

Duration, by contrast, refers either to the length of individual absence spells or to the total number of sickness absence days accumulated over a period (Bakker et al., 2003). This measure is of particularly high policy importance, because social security frameworks typically structure wage replacement, employer obligations, and insurance coverage according to the number of days or weeks a worker has been absent (OECD, 2020). In other words, duration determines not only how long workers remain out of work, but also under which compensation regime they fall at different stages of an absence spell; This allows for policy analysis of the sickness absence distribution.

These two measures, frequency and duration, can point in different directions. Older workers, for example, are often found to have fewer sickness absence spells but longer durations, which illustrates why analyses based only on total days absent may overlook important differences in reporting behaviour and underlying mechanisms. For the same reason, many studies distinguish explicitly between short-term and long-term sickness absence, since these are often associated with different diagnoses, decision processes, and policy sensitivities (Hensing, 1998; Čikeš et al., 2018).

A related measure is incidence rate, but goes a step further by relating sickness absence spells to person-time at risk, which becomes especially relevant in longitudinal designs where workers contribute different amounts of exposure time (Helsing, 1998). These measures are often better suited for epidemiological comparisons than simple totals, because they account more clearly for the population under observation and the contracted/scheduled time workers are actually at risk of becoming absent. However, the metric does however also require extensive planning data to account for the person-time at risk, which can be incomplete or biased.

The literature also warns that sickness absence measurement depends heavily on the data source. Self-reported absence is often easier to collect and can include contextual information unavailable in registers, but it is vulnerable to recall bias and declining accuracy as the recall period or number of absence days increases. Johns (2015) finds that self-reported absenteeism is reasonably reliable overall, but not perfectly accurate, while Stapelfeldt et al. (2012) show that administrative register data perform very well for longer certified spells but may miss or distort certain categories such as pregnancy-related absence depending on the registration system. These findings imply that administrative employer data are often preferable for precise measurement of spells and days, but that the institutional registration rules behind the data must be understood carefully. This measurement issue is especially important in cross-country research. Comparative studies often report national “sickness absence rates,” but these are not always directly comparable because institutional rules differ in waiting days, certification thresholds, employer-pay periods, and the point at which absence enters administrative registers. Palme and Persson (2019) explicitly note that observed cross-country absence measures are affected by differences in spell coverage and programme design, which limits straightforward causal interpretation.

For this thesis, the most useful takeaway is that no single measure captures “the” sickness absence phenomenon in full. Frequency-based metrics are especially informative when the interest lies in threshold-sensitive, short-term, or potentially discretionary absence. Duration-based metrics are more informative when the concern is burden, recovery time, or long-term work incapacity. Incidence measures are useful when the research question concerns the onset of sickness absence itself. A strong empirical design therefore requires matching the outcome measure to the mechanism under study, rather than treating all sickness absence metrics as interchangeable.

2.3 Policy

A substantial part of the policy-oriented sickness absence literature compares national institutional arrangements and relates them to differences in absence outcomes across countries. Palme and Persson (2019), for example, examine how measurable features of sick-pay insurance systems across European countries, such as replacement rates, waiting days, and duration limits, are associated with observed absence rates. Their analysis is grounded in insurance design and highlights how program rules may shape sickness absence behaviour through moral hazard mechanisms, policy incentive-sensitive behaviour. At the same time, they are explicit about the limits of this evidence, noting that cross-country absence measures are affected by institutional differences in spell coverage and therefore do not provide a clean basis for causal inference. Hall (2022) approaches the issue from a somewhat different angle by placing sickness insurance systems in the broader context of welfare-state regimes. Rather than focusing primarily on individual policy instruments, Hall compares how the generosity and structure of sickness insurance vary across regime types and whether these differences correspond to variation in national sickness absence rates. The study concludes that more generous systems tend to be related to higher sickness absence, while also emphasizing that such aggregate comparisons remain descriptive and do not adequately control for broader contextual differences between countries.

A related contribution is offered by Reuter and Gau (2025), who examine cross-country variation in presenteeism rather than sickness absence itself. Their study shows that sick-pay arrangements with at least 80% wage replacement for a minimum of two weeks are associated with an 8-percentage-point lower propensity for presenteeism. This finding illustrates that sick-leave policy can influence behaviour in more than one direction. Depending on how high or low the effective absence threshold is, policy may either create more scope for avoidable absence or reduce the pressure to attend work while ill. Distinguishing between these two effects is conceptually important, but empirically difficult, because both absence and presenteeism are shaped by overlapping institutional incentives.

At the same time, as their limitations also state, this comparative literature remains largely descriptive. National sick-leave institutions do not vary in isolation, but co-vary with labour market structures, sectoral composition, workplace norms, and employer practices. As a result, observed cross-country differences in sickness absence cannot easily be attributed to policy design alone. Higher absence in one country may reflect more generous benefits, but it may also reflect differences in job composition, worker health, reporting norms, or firm-level absence management. This limits the interpretability of broad country comparisons and leaves uncertainty about whether institutional effects are real or confounded by underlying work and workforce characteristics.

More convincing evidence on sickness absence responses comes from quasi-experimental studies that exploit policy reforms. Swedish evidence provides a clear illustration of these mechanisms. Voss (2001) evaluates the introduction of a waiting day and finds that sickness incidence declined after the reform. Henrekson et al. (2004) similarly analyse Swedish policy changes and show that institutional reforms affect not only the overall level of sickness absence, but also the composition of absence spells across different durations. This is an important result, because it suggests that policy does not simply change how much absence occurs, but also what kind of absence occurs.

Similar evidence exists for replacement-rate generosity. Ziebarth and Karlsson (2010) use German policy variation around benefit reductions to estimate the effect of lower replacement incentives and find that such reductions decrease sickness absence. Bockerman et al. (2018) report comparable effects for Finland, interpreting them as consistent with moral hazard behaviour. Together, these studies indicate that workers respond to financial incentives embedded in sick-pay systems, even when their health does not change mechanically as a result of the reform.

At the same time, the literature also points to important trade-offs. Marie and Vall Castello (2020), studying Spain, and de Paola et al. (2014), studying Italy, find that stricter incentives may reduce short-term absence while increasing long-term absence through relapses or workplace accidents. These results suggest that tighter rules can suppress discretionary or avoidable absence at one margin, but may also generate adverse effects if workers return too early or remain at work despite incomplete recovery. The policy problem is therefore not simply whether stricter incentives reduce absence, but whether they improve overall welfare and sustainable work participation.

Taken together, the policy literature shows that sick-leave institutions matter, but that their effects are most credibly identified when reforms allow researchers to observe behavioural responses at specific margins. Broad cross-country comparisons are useful for describing institutional variation and framing hypotheses, but they are less suited to isolating causal effects. The reform-based evidence suggests that waiting days, replacement rates, and other incentive-relevant rules can shift sickness absence in predictable ways. At the same time, the literature shows that lowering absence is not always equivalent to improving worker welfare, since reduced absence may partly come at the cost of higher presenteeism, relapse, or injury. This provides a clear rationale for examining Dutch sick-leave policy not only in terms of generosity, but also in terms of the incentive-sensitive behaviour it may induce.

2.4 Employee Characteristics

A first group of determinants concerns the employee profile. Across the sickness absence literature, individual characteristics repeatedly emerge as relevant correlates of absence behaviour, although the strength and direction of these relationships are not always consistent across studies and settings. In general, the literature suggests that part of the observed variation in sickness absence can be linked to differences in demographic composition, employment conditions, health-related background, and worker attitudes. For this reason, employee profile characteristics are important both as explanatory factors in their own right and as control variables in empirical analyses. In this study, these factors are considered employee characteristics because they capture differences between workers themselves, rather than differences in the immediate work environment or organizational context.

Determinant studies point to a relatively stable set of relevant individual-level correlates, including age, gender, tenure, contract conditions, worked hour arrangements, and job satisfaction, while also highlighting the role of health-related and household characteristics (Kristensen et al., 2006; Langenhoff et al., 2011). Systematic reviews confirm that these factors are among the most frequently studied predictors of sickness absence across sectors and countries, making them a useful starting point for hypothesis development and model specification (Beemsterboer et al., 2009; Čikeš et al., 2018).

Age and gender are among the most commonly examined determinants. The evidence on age is mixed. Beemsterboer et al. (2009) report that older workers tend to have lower absence frequency but longer absence duration, suggesting that age may affect not only whether workers call in sick, but also how long they remain absent once a spell begins. Čikeš et al. (2018) similarly conclude that age effects are not uniform across studies: in many cases younger workers show more absence, while in other settings older workers exhibit higher absence rates. This suggests that the relationship may be non-linear rather than strictly monotonic. For the present study, this implies that age should not be treated too simplistically, and that a specification allowing for non-linearity may be appropriate. Gender shows a more consistent pattern, with women often exhibiting higher sickness absence than men (Beemsterboer et al., 2009; Čikeš et al., 2018). Langenhoff et al. (2011) also find gender to be significant. In practice, gender differences may partly capture differences in household responsibilities, care obligations, or health-related reporting behaviour, although such mechanisms are often difficult to observe directly.

Tenure is another commonly included determinant, but here too the empirical evidence is less straightforward. Čikeš et al. (2018) describe the findings on tenure as mixed, with some studies reporting a positive association and others a negative one. Langenhoff et al. (2011) do not find tenure to be significant, but this may reflect model specification rather than the absence of a real effect. A plausible interpretation is that the relationship between tenure and sickness absence is non-linear: newly hired employees may display elevated absence because of adjustment issues or weaker attachment, while long-tenured employees may also show higher absence because of ageing, cumulative exposure, or changing work motivation. If such a pattern exists, a linear term alone may fail to capture it adequately.

Contract conditions are also frequently discussed in the literature. Čikeš et al. (2018) note that temporary contracts are often associated with lower absence than permanent contracts, while some studies find that part-time or casual work is linked to higher absence depending on the institutional and organizational context. Relatedly, Benavides et al. (2000) report that absenteeism is generally negatively associated with non-permanent employment. This is often interpreted as an incentive effect: workers with weaker job protection or less secure labour market positions may be less likely to report sick absence. However, Langenhoff et al. (2011) hypothesize that contract type is relevant but do not find a significant effect in their setting. One explanation is that contract effects are highly context-dependent and may be obscured when workers are not observed in sufficiently comparable work environments. This is especially relevant for the present thesis, where a within-firm and like-for-like design can help isolate contract effects more cleanly than cross-sector or cross-firm comparisons.

Closely related to contract type are contracted hours and broader working-time arrangements. The literature suggests that the scheduled number of hours matters for absence behaviour. Čikeš et al. (2018) summarize evidence that more contracted workdays, or a standard five-day workweek, are associated with lower absence than shorter workweek arrangements. This indicates that working-time structure may shape both the practical opportunity and the behavioural threshold for taking sick leave. In a logistics context, contracted hours may also proxy for labour market attachment, financial dependence on work, or exposure to demanding schedules, making them relevant controls in any model of sickness absence.

Health-related factors are also frequently identified as important predictors. Beemsterboer et al. (2009) report that smoking and alcohol consumption are associated with higher sickness absence, while higher education and greater satisfaction with private circumstances are associated with lower and shorter absence. Langenhoff et al. (2011) similarly find that health-related variables such as BMI and smoking are significant. These findings are important, but they also reveal a practical challenge for empirical research: such information is often unavailable at the individual level due to privacy restrictions. For firm-level administrative analyses, this means that directly modelling health status is often impossible. One implication is that large sample sizes may partly average out unobserved health heterogeneity, but omitted-variable bias remains a concern. Where direct health indicators are unavailable, the analysis may need to rely on indirect proxies or acknowledge this limitation explicitly.

Household and private-life characteristics form another relevant, though often difficult-to-measure, group of determinants. Beemsterboer et al. (2009) find that married workers tend to have lower and shorter sickness absence, and that satisfaction with private circumstances is associated with less absence. Langenhoff et al. (2011) also reports significance for household characteristics. However, such variables are often not accessible in employer data. In the context of Picnic's workforce, some of these effects may partly overlap with age composition, since household formation, care burdens, and private-life stability are correlated with life stage. This again underlines the importance of careful interpretation when only a limited set of employee characteristics is available.

Distance to work is less prominent in the classic absence literature, but may still matter through commuting burden and mode of transport. Recent evidence suggests that commuting conditions can influence sickness absence: Kalliohoti et al. (2024), for example, find that regular active commuting by bicycle is associated with a lower risk of long sickness absence episodes. This points to a potentially relevant mechanism linking commuting patterns, physical activity, and health resilience. In practice, distance to work may therefore serve as a useful employee-level characteristic, even if its effect is likely to be indirect and sensitive to local infrastructure and transport mode.

Finally, job satisfaction stands out as one of the most robust predictors in the literature. Both Beemsterboer et al. (2009) and Čikeš et al. (2018) identify job satisfaction as a consistent negative correlate of sickness absence: higher job satisfaction is generally associated with lower absence frequency and shorter absence duration. Langenhoff et al. (2011) also finds job satisfaction to be significant. At the same time, this relationship should be interpreted with caution, since job satisfaction may be partly endogenous to the work environment, management, scheduling conditions, or prior absence experiences. It may therefore capture not only an individual attitude, but also broader workplace experiences that overlap with the mechanisms shaping sickness absence. For that reason, job satisfaction can still be a relevant variable to include in the present study, but less as a purely exogenous determinant and more as an indicator of how employees experience their work situation.

Taken together, the policy literature shows that sick-leave institutions matter, but that their effects are most credibly identified when reforms allow researchers to observe behavioural responses at specific margins. Broad cross-country comparisons are useful for describing institutional variation and framing hypotheses, but they are less suited to isolating causal effects. The reform-based evidence suggests that waiting days, replacement rates, and other incentive-relevant rules can shift sickness absence in predictable ways, consistent with the earlier absence-threshold perspective in which institutional arrangements influence the threshold at which workers convert impaired health, fatigue, or competing pressures into reported absence. At the same time, the literature shows that reducing sickness absence is not automatically welfare-improving, since lower absence may partly come at the cost of higher presenteeism, relapse, or injury. This provides a clear rationale for examining Dutch sick-leave policy not only in terms of generosity, but also in terms of the behavioural responses and welfare trade-offs it may generate.

2.5 Job Context

Beyond employee profile characteristics, the literature also points to several aspects of the immediate job context that may shape sickness absence. While these factors are conceptually distinct from demographic and contractual characteristics, they are relevant here because they affect the day-to-day work experience of otherwise comparable employees and may therefore help explain residual variation in absence behaviour within similar worker groups. Work schedule characteristics appear to matter especially where working time is irregular or operationally demanding. Nicholson et al. (1978) show that absence patterns vary by "shift-turn" or shift-time (morning, afternoon, or night shift), day of the week, and position in the shift cycle, indicating that the temporal organization of work itself influences absence behaviour. Adjectantly, Dionne and Dostie (2007) find that standard weekday work hours are associated with lower absence, whereas shift work and compressed work weeks are associated with higher absence. Taken together, these findings suggest that regular and predictable schedules tend to reduce sickness absence, while non-standard or more disruptive scheduling structures may increase it. However, the literature remains relatively coarse in how it captures operational work patterns. Fine-grained variables such as planned hours per week, hours worked per shift type, time between shifts, or available hours per week are largely absent from the classic sickness absence literature. For an operational logistics setting, these variables may therefore offer useful extensions to existing models rather than merely replications of prior work.

Leadership and supervisory context also emerge as important job-related determinants. Several studies show that supportive leadership by supervisors are associated with lower sickness absence (Chullen et al., 2010; Hassan et al., 2014; Iverson et al., 1998). By contrast, passive-avoidant leadership is associated with higher absence (Frooman et al., 2012). Tharenou (1993) similarly finds that supervisory style is negatively associated with uncertified absence, or No-shows. These findings suggest that the local management environment can influence attendance both directly, for example through support and monitoring, and indirectly, through morale, perceived fairness, and commitment. In practice, this means that leadership-related variables may be important controls when explaining sickness absence variance across teams, shifts, or sites.

A related but less frequently discussed aspect of job context concerns lateness and job performance. In the organisational-withdrawal literature, lateness is often treated as a behaviour related to absenteeism rather than as a wholly separate phenomenon. Meta-analytic evidence shows that employee lateness and absenteeism are positively associated, suggesting that recurrent lateness may reflect a broader pattern of attendance problems or reduced attachment to work (Koslowsky et al., 1997; Berry et al., 2012). Job performance appears to be linked to sickness absence in a more indirect way. Rather than pointing to a simple causal relationship, the literature suggests that performance, work functioning, and sickness absence are related outcomes shaped by overlapping influences such as health, work demands, and perceptions of work (Wynne-Jones et al., 2009). For the present study, this implies that both lateness and performance may be useful indicators of the immediate work context when data on health, work demands, and perceptions of work is not included in the model.

Finally, human resource practices and broader workplace management appear to shape absence behaviour as well. Boon et al. (2014) find that positive perceptions of HR practices are associated with lower absenteeism, partly through higher job satisfaction. Likewise, Johnson et al. (2014) and Kopelman and Schneller (1981) show that absence control systems and policy interventions can alter absence outcomes, although effects may differ by type of absence. This suggests that HR context should not be seen purely as background administration, but as part of the incentive and support structure in which attendance decisions are made. For the present study, this is particularly relevant because variation in site-level management practices, staffing arrangements, or local HR implementation may affect absence behaviour even within the same national regime and firm.

Overall, the literature suggests that job context adds an important layer to the employee profile perspective. Whereas profile variables such as age, gender, tenure, and contract conditions capture who the worker is, job-context variables capture the conditions under which comparable workers perform their job. In the existing literature, the strongest evidence concerns schedule structure, job satisfaction, leadership, and HR practices. At the same time, many operationally relevant variables, such as detailed shift timing, staffing intensity, or hours actually worked, remain underexplored. This makes them particularly relevant to include in a logistics-based analysis, where the immediate work context is likely to play a central role in shaping sickness absence.

Weekdays were already shown to have a significant relationship with sickness absence, a second timing-related factor concerns holidays, weather events, extended weekends, and cultural events. Following semi-structured informal interviews with HR at Picnic, concerns were raised that sickness absence may also follow these broader calendar-based patterns. Such patterns are difficult to explain from a purely health-based perspective, since the timing of holidays or cultural events does not in itself alter underlying health needs. They may, however, affect the practical and behavioural context in which workers decide whether to report sick.

The existing literature does not yet provide strong evidence that such timing patterns systematically increase sickness absence. Research in this area remains limited. One relevant study is Böheim and Leoni (2020), who examine so-called bridging days, defined as Mondays or Fridays that fall between a weekend and a public holiday. In theory, these days create an opportunity to extend leisure and could therefore increase the incentive for avoidable sickness absence. Using longitudinal social security data covering private-sector employees in a large Austrian region over eleven years, however, the authors find no evidence of inflated sickness absence on bridging days. On the contrary, sickness rates are consistently lower on bridging days than on regular Mondays and Fridays, and the authors interpret this pattern as being more consistent with workers taking vacation than strategically reporting sick.

2.6 Exogeneous

Beyond institutional, employee, and job-context determinants, sickness absence may also be shaped by exogenous and contextual sources of variation. These factors are relevant because they can affect observed absence independently of firm-level practices or national policy incentives. If they are not accounted for, differences in sickness absence may be incorrectly attributed to institutional or organisational mechanisms.

A first source of variation concerns epidemiological shocks, especially influenza and influenza-like illness. The literature shows that absenteeism tends to rise during influenza epidemics and often tracks epidemic peaks relatively closely (Szucs, 1999; Groenewold et al., 2013). This makes influenza an important contextual factor in sickness-absence research. If influenza peaks are not accounted for, temporary increases in absence may be misinterpreted as changes in employee behaviour, firm operations, or institutional incentives. This is particularly important in cross-country analysis, since the timing and intensity of influenza seasons may differ across countries and years, meaning that part of the observed difference in sickness absence may reflect different epidemiological conditions rather than different absence behaviour or policy regimes (Vega et al., 2015).

A second source of variation concerns labour-market tightness and broader economic conditions. The literature suggests that sickness absence is related to the business cycle: absence tends to be lower when unemployment is high and higher when labour markets are tighter, although the mechanisms may include both compositional effects and behavioural responses to job insecurity or workload (Askildsen et al., 2005; Pichler, 2015; Blomgren et al., 2021). This matters for the present study because differences in national or local labour-market conditions may influence absence behaviour independently of company-level operations or formal sick-leave rules. In periods of labour-market tightness, workers may face different outside options, workload pressures, or job-security perceptions, all of which may affect the threshold at which sickness absence is reported.

A third source of variation concerns major operational disruptions. Through informal interviews with HR at Picnic, it became clear that sudden disruptions in logistics operations may also shape sickness absence. Examples include unusually weather events, high workload, staffing shortages, system failures, delivery delays, demand peaks, or other events that temporarily alter the work environment. These disruptions may influence absence behaviour in different directions. Higher workload or operational stress may increase fatigue, strain, or perceived work pressure, while acute staffing needs and team dependency may also increase attendance pressure. Major operational disruptions are therefore relevant because they may change both the actual burden of work and the threshold at which employees report sick.

2.7 Conclusions and implications for this research

The literature reviewed in this chapter shows that sickness absence should be understood as a complex and multidimensional outcome, rather than as a direct reflection of illness alone. Although sick leave is institutionally intended to protect workers during periods of genuine work incapacity, observed sickness absence also reflects organisational conditions, administrative rules, social norms, and behavioural choices. This implies that sickness absence is not simply a measure of health, but the outcome of a reporting process shaped by the broader context in which workers decide whether to remain at work or report sick.

A first implication for this research is therefore conceptual. The literature suggests that sickness absence contains different margins that should be distinguished analytically. At one end lies legitimate recovery absence, which is consistent with the core protective purpose of sick leave. Around that lies an avoidable margin, part of which remains health-related because it arises from preventable working conditions or exposures, and part of which may be more strongly shaped by financial incentives, administrative requirements, social norms, or private circumstances. The absence-threshold perspective is particularly useful here, because it explains why employees with comparable health complaints may make different reporting decisions depending on the costs, obligations, and norms surrounding sickness absence. For the present study, this means that differences in sickness absence should not automatically be interpreted as differences in underlying health alone.

A second implication concerns measurement. The literature shows that sickness absence can be operationalised in different ways, and that these measures are not interchangeable. Frequency, duration, and absence rate each capture a different aspect of the phenomenon and are suited to different research questions. Frequency is particularly relevant for understanding how often employees cross the threshold into reported sickness absence, where absence rate controls this measrre for the amount of exposed hour. While duration is more closely connected to recovery time, employer burden, and policy design, since employer obligations and wage replacement often depend on time spent absent. For this research, the choice of sickness-absence indicator should therefore follow the mechanism of interest rather than be treated as neutral. Policy levers are also expected to operate at different parts of the absence process: some mainly affect the decision to report sick, while others are more likely to affect the duration of absence and the timing of return to work.

At the institutional level, the reviewed literature identifies three main policy levers that are especially relevant for this thesis: waiting days, wage replacement rates, and doctor's note or certification requirements. These levers shape sickness absence behaviour by changing the financial, administrative, and verification conditions under which employees decide whether to report sick and when to return to work. Importantly, these levers are expected to operate at different margins of absence. Based on the literature, the following policy-lever propositions arise.

First, waiting days are expected to be associated with lower short-term absence frequency. The mechanism is that waiting days increase the immediate financial cost of reporting sick, especially for short spells. This raises the threshold at which minor health complaints, fatigue, or private circumstances are translated into a formal sickness absence report. This expectation follows directly from the absence-threshold perspective of Allegro and Veerman (1998), in which sickness absence is shaped not only by health, but also by incentives, constraints, and norms. It is also supported by reform-based evidence from Voss (2001), who finds that the introduction of a qualifying or waiting day reduced sickness incidence, and by Henrekson and Persson (2004), who show that sickness-insurance reforms affect both the level and composition of absence spells. Therefore, the first proposition for this research is that stricter waiting-day rules are expected to reduce absence mainly at the short-term frequency and absence-onset margin, rather than at the long-term recovery margin.

Higher wage replacement rates are expected to be associated with higher absence persistence and longer absence duration. The mechanism is that generous income protection lowers the financial cost of remaining absent. This expectation is consistent with comparative evidence from Palme and Persson (2019) and Hall (2022), who relate more generous sickness-insurance arrangements to higher sickness absence, and with reform-based evidence from Ziebarth and Karlsson (2010) and Böckerman et al. (2018), which shows that reductions in sick-pay generosity reduce sickness absence. For this thesis, wage replacement is therefore expected to matter especially for the duration and return-to-work margin, particularly around points where the effective replacement rate changes during an absence spell. At the same time, this proposition should not be interpreted as implying that all additional absence under generous replacement is illegitimate. Reuter and Gau (2025) show that generous sick pay may also reduce presenteeism, meaning that high replacement rates can support legitimate recovery while also increasing the scope for longer or more avoidable absence. Therefore, the second proposition is that higher wage replacement rates are expected to be associated with longer absence duration and greater absence persistence, especially when the replacement rate remains high during the early or medium-term stages of sickness absence.

Stricter doctor's note or certification requirements are expected to be associated with lower short-term absence frequency. The mechanism is that certification requirements increase the administrative and verification burden of reporting sick. This is especially relevant for short-term or uncertified absence, where the decision to report sick is more likely to be influenced by discretion, convenience, and perceived monitoring. This expectation is supported by Tharenou (1993), who links short-term absence more closely to discretionary attendance behaviour than longer certified absence. It is also consistent with evidence on monitoring and verification from Boeri et al. (2021), who show that home visits during sick leave can reduce subsequent absence. Therefore, the third proposition is that stricter certification requirements are expected to reduce sickness absence mainly at the short-term absence-onset margin, where reporting thresholds and verification costs are most likely to affect behaviour, rather than at the long-term recovery margin.

A third implication concerns employee characteristic, the reviewed literature shows that variation in sickness absence cannot be explained by institutional policy alone. Employee characteristics such as age, gender, tenure, contract type, contract-hour arrangements, and job satisfaction recur as relevant correlates of sickness absence, although their effects are not always consistent across settings. These determinants are important because they may influence both underlying health risks and the threshold at which employees decide to report sick. For example, differences in tenure or contract type may reflect differences in job security, attachment to the organisation, or familiarity with reporting procedures, while age and gender may partly capture differences in health, care responsibilities, or labour-market position.

In addition, the literature suggests that the immediate work context can shape sickness absence behaviour. Factors such as shift structure, leadership, HR practices, lateness, and performance-related indicators may help explain differences in absence among otherwise comparable workers. These variables are relevant because they capture how work is organised and experienced in practice. For this research, this means that individual and operational factors should be included alongside national policy levers, not as alternatives to policy explanations, but as complementary determinants. They help assess whether observed differences in sickness absence are related to institutional incentives, employee composition, or the specific conditions under which work is performed.

A final implication concerns exogenous variation. The literature and professionals from the logistics' sector indicate that observed sickness absence may also be shaped by factors outside the direct control of firms or policy design, such as influenza peaks, labour-market tightness and major operational disruptions. These factors may influence sickness absence in different ways: some reflect genuine changes in health risk, while others shape the practical or behavioural context in which absence decisions are made. For this research, such variables are relevant because they help prevent observed absence differences from being too quickly attributed to institutional or organisational mechanisms alone.

Taken together, these insights imply that the present study should bring together concept, measurement, explanation, and context. Sickness absence must first be understood as a layered phenomenon; it must then be measured in a way that matches the research question; and variation in it must be analysed through a combination of institutional, individual, job-context, and exogenous factors. The resulting expectations are that waiting days and certification requirements mainly affect whether employees report short-term sickness absence, while wage replacement rates mainly affect how long employees remain absent and when they return to work. This integrated perspective provides the foundation for the empirical analysis and for the conceptual model developed in the remainder of this thesis. Rather than making causal claims or diagnosing specific types of absence directly, the thesis uses this framework to develop a more complete system-level understanding of what factors may shape sickness absence behaviour and how they may operate in practice.

2.8 Conceptual model

Figure 4 presents the conceptual model derived from the literature review and aligned with the empirical strategy of this study. The model treats sickness absence as the central outcome of interest and reflects the main conclusion of the review: sickness absence should not be understood as a direct expression of illness alone, but as an outcome shaped by multiple layers of influence. In the figure, these influences are grouped into individual factors, exogenous factors, and policy, while sickness absence itself is represented as a layered outcome consisting of total sickness absence, avoidable absence, and discretionary absence. This layered structure helps interpret the possible nature of observed sickness absence behaviour, while keeping the empirical focus on total observed absence and its associated determinants.

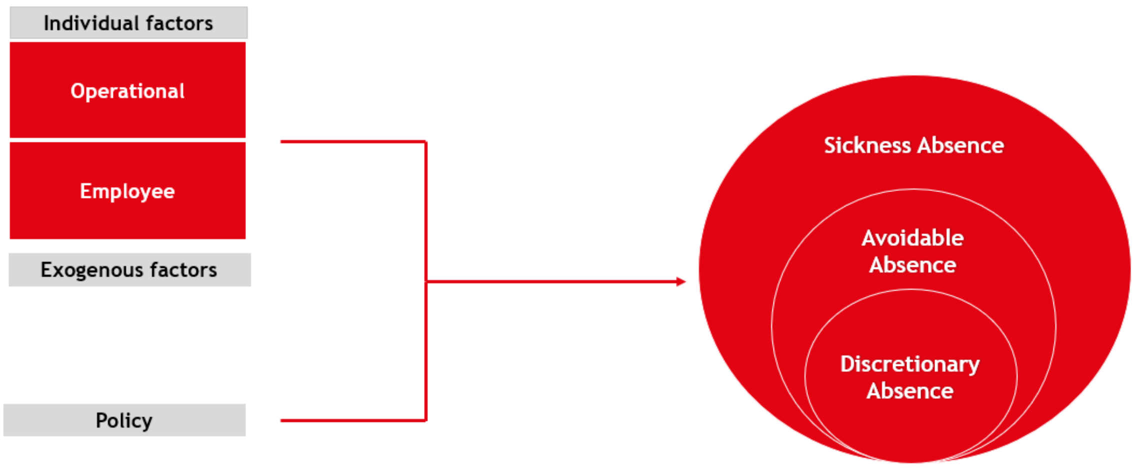

Figure 3: Conceptual model

On the left-hand side, the model distinguishes between two categories of individual factors: **Employee characteristics** and **operational factors**. Employee-related factors capture who the worker is, including characteristics such as age, gender, tenure, contract type, contracted hours, commuting conditions, and job satisfaction. Work-related factors capture the immediate context in which the worker performs the job, such as shift structure, leadership, HR practices, lateness, and performance-related indicators. This distinction follows directly from the literature review. Both groups of variables are relevant to sickness absence, but they capture analytically different dimensions. Employee-related factors mainly reflect differences in worker composition, whereas work-related factors reflect differences in the organisation and experience of work among otherwise comparable workers.

These individual factors are included because they operate as proximate determinants of sickness absence at worker level. They help explain why one worker, or one worker in one work context, may display different absence behaviour than another. At the same time, the literature suggests that these variables do not all operate through the same mechanism. Some factors, such as age, health-related background, or commuting burden, may influence sickness absence through underlying health risk or recovery needs. Others, such as contract security, job satisfaction, or aspects of work organisation, may affect the absence threshold: the point at which reduced health, fatigue, strain, or competing pressures are translated into reported absence. The model therefore groups these variables together as worker-level explanatory factors while recognising that they may affect sickness absence through both health-related and behavioural pathways.

In addition to these worker-level determinants, the model includes **exogenous factors**. These are influences that are external to the worker and the immediate work setting, but that may still affect observed sickness absence. Examples include influenza waves, labour-market tightness, and major operational disruptions such as events, weather, and system failures. Such factors may alter the broader conditions under which sickness absence occurs. Influenza, for example, may raise genuine illness incidence, whereas labour-market tightness may affect job-security perceptions, outside options, workload pressures, or employer-employee bargaining conditions.

Policy is positioned separately from both individual and exogenous factors. This reflects the analytical setup of the study, in which policy is not treated simply as another contextual determinant, but as a distinct institutional dimension. Policy variables, such as waiting days, replacement rates, certification requirements, and employer obligations, define the formal rules and incentives surrounding sickness absence. They shape the framework within which workers, firms, and managers operate, but are analysed separately from the worker-level and exogenous determinants. In that sense, policy is treated as a separate institutional layer that may shape sickness absence behaviour through incentives, constraints, and norms.

On the right-hand side, the model presents **sickness absence as a layered outcome**. The outer circle represents total observed sickness absence. Within this lies avoidable absence, referring to the share of absence that may be preventable, incentive-sensitive, or linked to conditions that could in principle have been altered. Avoidable absence should not be equated with illegitimate absence. Part of it may still involve legitimate recovery absence where a worker is genuinely ill and requires time to recover, while the underlying causes of that illness may nevertheless be linked to preventable working or organisational conditions. Within the avoidable margin lies discretionary absence, representing a narrower category of absence behaviour that may be more sensitive to judgement, norms, private circumstances, and situational incentives. The nesting of the circles indicates that discretionary absence can be understood as a subset of avoidable absence, which is itself a subset of total sickness absence. Presenteeism can't be measured directly, because by definition it is unregistered sickness. This is therefore not included in the conceptual model, it will however be included in interpretation of results.

An important implication of this structure is that the determinants included in the model are not expected to affect sickness absence in one uniform way. Some variables may relate more strongly to general sickness absence because they capture illness risk, recovery needs, or exposure to health shocks. Others may be more closely connected to the behavioural threshold through which workers translate health complaints, fatigue, strain, or private circumstances into reported absence. Policy and organisational conditions may matter especially where absence behaviour is responsive to incentives, constraints, or workplace norms. Exogenous factors, such as influenza waves, labour-market tightness, operational disruptions, and calendar-based events, may shape either underlying health risk or the broader context in which absence decisions are made. The conceptual model therefore allows different factors to operate through different mechanisms, without assuming that these mechanisms can always be cleanly separated empirically.

Finally, the model remains deliberately simplified. It does not claim that all variables act independently or that all pathways can be fully separated. In reality, many of the relationships identified in the literature are interrelated, and some determinants may also be endogenous to the absence process itself. The purpose of the conceptual model is therefore not to depict every possible interaction, but to provide a structured representation of the main relationships identified in the literature and to guide the analytical choices made in the remainder of the study. In this way, the layered structure helps interpret the possible nature of observed sickness absence behaviour, while the empirical analysis remains focused on total observed absence and the institutional, individual, organisational, and exogenous factors associated with it.

3 Research Methods

The empirical analysis follows a stepwise logic. First, the institutional policy analysis maps the sickness absence frameworks in the Netherlands, Germany, and France and derives expected absence patterns at specific margins of the absence distribution. Waiting days and certification requirements are expected to matter mainly for short-term absence and absence frequency, while wage replacement and employer obligations are expected to matter more for long-term spell duration. Second, exploratory analyses compare these expectations with observed absence frequency and duration patterns, and identify relevant worker-profile and operational differences. Third, multivariate regression models examine whether sickness absence remains associated with employee characteristics, job and operational context, and exogenous factors after controlling for other variables. OLS models are used for the weekly absence rate because this outcome captures the total absence burden. Survival analysis is used for sickness spell duration because it captures return-to-work dynamics once an absence spell has started. Finally, the findings are synthesised into an operational and policy strategy foundation by distinguishing recurring operational patterns from country-specific patterns.

Table 1: Empirical logic linking research questions, outcomes and methods

Research question	Empirical focus	Outcome	Method	Interpretation
SQ1	National sickness absence frameworks and observed absence patterns	Absence frequency and spell-duration distributions	Exploratory policy analysis	Assesses whether observed patterns are consistent with expected policy-incentive margins.
SQ2	Individual, operational and exogenous drivers of sickness absence	Weekly sickness absence rate	OLS regression, with person-level robustness OLS	Identifies factors associated with the total absence burden.
SQ2	Persistence of sickness absence once a spell has started	Spell duration / return-to-work	Kaplan–Meier curves and Cox proportional hazards models	Identifies factors associated with shorter or longer sickness spells.
SQ3	Translation of findings into evidence base for action and policy reflection	Recurring and country-specific patterns	Cross-country synthesis	Distinguishes operationally actionable patterns from patterns that appear more country- or policy-specific.

3.1 Data

This study uses individual-level administrative and operational data from Picnic to analyse sickness absence among employees in the Netherlands, Germany, and France. The primary observation period runs from 1 January 2024 to 31 December 2025. In addition, data from December 2023 are included where necessary to construct lagged independent variables for January 2024. This is relevant for variables that depend on prior employee behaviour or prior operational conditions, such as previous absence, lateness, performance, or recent shift characteristics.

The observation period is restricted to 2024–2025 for two reasons. First, the core statutory sick-pay regimes in the Netherlands, Germany, and France were not subject to major redesign during this period. The institutional arrangements were cross-checked using national government sources and MISSOC comparative tables (MISSOC, 2026). One relevant exception is the French April 2024 reform on paid leave accrual during sick leave, which is included in the institutional mapping but does not alter the empirical definition of sickness absence spells used in the regression models. Second, Picnic experienced rapid organisational growth during the broader period, including continued expansion in Germany and France. A longer observation window could therefore introduce additional organisational variation that is less comparable across countries and time (Picnic, 2025).

The empirical scope is limited to employees with a direct Picnic contract. Temporary employment agency workers are excluded for methodological and administrative reasons. Data availability for agency workers is more limited, and including them would have resulted in many incomplete observations that would need to be dropped from the analysis. This could introduce bias and reduce the comparability of the dataset. The analysis is further restricted to Shoppers and Runners, as these are the two largest operational job profiles within Picnic and represent core warehouse and delivery activities that are central to logistics operations. Shoppers are responsible for replenishing the stock in the warehouse and assembling the groceries for customers, while Runners are responsible for delivering the groceries to the customers' home. The specific activities of each worker can differ slightly per location.

Shoppers and Runners are analysed separately throughout the empirical analysis. This choice is motivated by both theoretical and methodological considerations. The literature review shows that job characteristics are important determinants of sickness absence, and combining both job profiles in a single model would introduce additional variation that is not the main focus of this thesis. Moreover, the work circumstances of Shoppers and Runners differ substantially, meaning that not all explanatory variables apply equally to both groups. For example, shift type and shift-specific operational conditions are relevant for Shoppers, but not directly applicable to Runners in the same way.

The dataset consists of Shoppers and Runners. This results in observations on a person-week level for the absence-rate OLS models discussed in the next section. This size provides a detailed view of sickness absence behaviour over time, while also allowing lagged behavioural and operational variables to be included. At the same time, this level of detail introduces several methodological limitations, which are discussed in Chapter 7. Sources for each dataset are discussed in Appendix I.

Constructed datasets

The resulting datasets are adjusted to fit the purpose of each part of the analysis. Because the thesis combines institutional policy mapping with quantitative regression analysis, different data structures are required for different analytical steps. The policy analysis relies primarily on institutional and legal information, supported by descriptive absence patterns. The quantitative analysis uses three constructed datasets: a person-week-level dataset for the main absence-rate OLS models, a person-level aggregated dataset for robustness checks, and an absence-spell dataset for the survival analysis of sickness spell duration. Each dataset contains roughly the same variables, however they have been adjusted to an average, a time-dependent variable or a time-dependent lagged variable to match the structure of the dataset. Specifications of the operationalization have been placed in Confidential Annex J, and can not be shown in this version due to company-sensitive data.

Exploratory Institutional Policy-analysis: The institutional policy analysis maps and compares the sickness absence systems in the Netherlands, Germany, and France. This part of the research is based on authoritative legal and policy documentation, comparative institutional sources, and internal input from Picnic's HR. The analysis focuses on institutional features such as sick-pay arrangements, waiting days, employer obligations, certification requirements, reintegration rules, and employee incentives. Policy elements are cross-checked across at least two sources where possible. Exceptions, eligibility conditions, waiting periods, employer obligations, and scope limitations are documented explicitly. This policy information is analysed separately from the individual-level regression models, but it provides essential context for interpreting cross-country differences in absence behaviour. For the observed sickness absence, the data used is structured at the absence-spell level. Each observation represents one sickness absence spell. For further explanation of the operationalization of absence duration, see Section 3.2.

3.2 Operational Sickness Absence definitions and formulation

To operationalise sickness absence, this study uses three complementary concepts: the sickness absence rate, absence duration, and absence frequency. Together, these concepts capture different dimensions of sickness absence behaviour. The sickness absence rate reflects the share of expected working time lost due to sickness absence, duration captures the length of sickness absence spells, and frequency reflects how often new sickness absence spells occur.

Absence frequency is used descriptively, but not modelled as a separate dependent variable, because a clean frequency model would require comparable time-at-risk across employees. Since employees differ in employment duration, contract size, scheduling intensity and observed exposure, a simple count of sickness spells would conflate absence behaviour with opportunity to become absent. Previous studies that did use frequency as a dependent variable used aggregated data, and assumed generally equal exposure. In this granular individual dataset, such an assumption is not possible.

The empirical analysis focuses on the two other main absence outcomes. The sickness absence rate is used in the OLS regression models, both at the person-week level and in the person-level aggregated robustness model. Absence duration is used in the survival analysis.

Sickness absence rate is defined as the share of expected working time that was lost due to sickness absence within a given observation period, in this study. For the main OLS analysis, the observation period is the employee-week. At the employee-week level, the sickness absence rate is defined as:

$$AR_{it} = \frac{AH_{it}}{EH_{it}} \tag{1}$$

where AR_{it} denotes the sickness absence rate of employee i in week t, AH_{it} is the number of sickness absence hours recorded for that employee-week, and $EH_{it}$is the number of expected working hours in the same employee-week.

This measure is preferred over a simple frequency headcount-based measure because employees differ in expected labour input. Contracted hours, planned shifts, and actual working patterns vary across employees. Measuring sickness absence relative to expected hours therefore provides a more precise and unbiased indicator of the share of work time lost. Expected working hours are based on planned, contracted, or expected working time, depending on the contract-type of the employee. This allows sickness absence to be measured consistently across employees with different contract structures and working patterns.

For the person-level robustness OLS, the same logic is applied over the full observed period. The person-level sickness absence rate is defined as:

$$AR_i = \frac{\sum_t AH_{it}}{\sum_t EH_{it}} \tag{2}$$

where AR_idenotes the sickness absence rate of employee i over the full observation period, $\sum_t AH_{it}$ is the employee's total sickness absence hours, and $\sum_t EH_{it}$ is the employee's total expected working hours. This formulation creates one absence-rate outcome per employee and is used to assess whether the main OLS findings remain consistent when repeated person-week observations are removed.

At the aggregate level, the sickness absence rate for a population or group is calculated as total sickness absence hours divided by total expected working hours:

$$AR_{\text{pop}} = \frac{\sum_i AH_i}{\sum_i EH_i} \tag{3}$$

where AR_{pop} denotes the sickness absence rate for the full employee population. This formulation weights employees by expected labour input rather than by simple employee counts.

Absence duration is measured at the spell level and captures the length of a sickness absence spell in calendar days. This measure is used in the survival analysis, where the focus is on how long sickness spells last.

For sickness spell j, duration is defined as:

$$D_j = e_j - s_j + 1 \tag{4}$$

where D_j denotes the duration of sickness spell j, s_j is the recorded start date of the spell, and e_j is the recorded end date. The addition of one ensures that both the first and final day of the sickness spell are included.

For the Netherlands, the duration measure used in the policy analysis accounts for the Dutch four-week spell-chain-linking rule. Under this rule, a new sickness absence registration that starts within four weeks of recovery from a previous sickness spell is treated institutionally as a continuation of the earlier sickness case rather than as a separate new case. Therefore, for policy-based duration comparisons, Dutch sickness episodes separated by less than four weeks are linked into one continuous case. This reflects the Dutch institutional definition and prevents short interruptions from artificially reducing policy-based duration measures. However, this linking rule is not applied in the survival analysis. The survival analysis uses observed sickness absence spells as recorded in the operational data, because linking separate registrations would alter the observed duration process, reduce the number of observed spell-ending events, and make Dutch spell durations less comparable to the observed spell structures in Germany and France.

Absence Frequency captures how often new sickness absence spells occur during a given period. Absence frequency refers to the start of a new sickness absence spell and is only used in aggregated decriptive for aforementioned reasons. Over a longer observation period, absence frequency can be calculated as the total number of sickness absence spells started by an employee:

$$F_i = \sum_t N_{it}^{\text{start}} \tag{5}$$

where F_i denotes the total number of sickness absence spells started by employee i during the observation period. The average absence frequency across a population can be expressed as:

$$\hat{F} = \frac{1}{E} \sum_i F_i \tag{6}$$

where $\hat{F}$ is the average number of sickness absence spells started per employee, and E is the total number of employees in the study population.

Average absence frequency over the full observation period is calculated only for employees who were employed during the entire relevant timespan. This ensures that all included employees had the same opportunity to record absence spells. Employees with partial employment during the period are excluded from this aggregate frequency measure to avoid confounding absence frequency with differences in exposure time. The Dutch four-week spell-chain-linking rule is applied to duration-based analysis, but not to descriptive observed onset counts unless explicitly stated. This distinction is important because the linked-spell definition is designed to measure legally and administratively continuous sickness episodes, while observed onset counts describe when employees newly report sickness absence.

The sickness absence rate can be interpreted as the combined result of how often sickness absence occurs and how long sickness spells last. Conceptually, a higher absence rate may arise because employees start sickness spells more often, because spells last longer, or because both frequency and duration increase.

$$\text{Absence rate} \approx \text{Absence frequency} \times \text{Average absence duration} \tag{7}$$

This relationship is used as a light interpretive framework in the final synthesis of the findings. The OLS models identify factors associated with the overall absence burden, while the survival models identify factors associated with spell duration. When a factor is associated with the absence rate but not with longer spell duration, this may suggest that the factor is more related to absence occurrence or short-term absence behaviour. When a factor is associated with longer spell duration, this may point more towards recovery, reintegration, or case-management processes. Still, this interpretation is used cautiously and does not classify individual sickness absence cases directly.

3.3 Exploratory analyses

3.3.1 Policy analysis

SQ1 uses a mapping of the institutional sickness absence regimes in the Netherlands, Germany, and France to do an empirical assessment of of absence distribution. For each country, the mapping documents the main institutional levers that may shape sickness absence behaviour:

1. waiting/qualifying days,
2. Replacement-rate schedule over time,
3. Duration of employer payment obligations,
4. Eligibility/certification requirements (including doctor's note rules),
5. Spell-linking rules and other relevant social-security framework conditions.

The empirical part of SQ1 starts with distributional analysis rather than relying only on aggregate absence rates. This is important because sickness absence is multidimensional: some measures capture how often workers report sick, while others capture how long they remain absent once a spell has started (Hensing, 1998; Beemsterboer et al., 2009; Duchemin et al., 2020). The policy analysis therefore compares absence frequency and duration patterns across the Netherlands, Germany, and France within broadly comparable logistics frontline operations. This includes descriptive plots of absence frequency per country and role, as well as duration distributions using histograms and categorised duration bins.

This distinctive distribution and frequency approach is important because the different policy levers are expected to matter at different points in the absence distribution. Waiting days and certification requirements are expected to affect the threshold for reporting sick and are therefore most relevant for short-term absence and frequency. Wage replacement rates, employer payment obligations, and reintegration rules are more relevant for return-to-work behaviour and longer absence durations. This distinction follows the broader sickness absence literature, which treats absence occurrence and absence duration as related but analytically different processes (Hensing, 1998; Koopmans et al., 2009; Duchemin et al., 2020).

Additional plots are used where needed to make these comparisons more precise. These include subgroup analyses where policy rules differ within a country or apply differently across employee groups. For example, the Dutch waiting-day rule differs depending on whether an employee has been sick in the previous six months, while certification requirements in Germany and France differ between Shoppers/Runners and Captains/Leads. Such subgroup analyses help assess whether observed absence patterns are concentrated in the groups or duration margins where specific policy levers would be expected to matter most.

The aim of SQ1 is therefore not only to describe institutional differences, but to connect each policy lever to observed absence patterns. This provides the policy foundation for interpreting later regression results and for assessing which aspects of the national sickness absence systems appear most relevant for observed absence behaviour and return-to-work patterns. The policy analysis remains interpretive rather than causal: it is used to identify plausible institutional mechanisms, not to estimate definitive policy effect sizes.

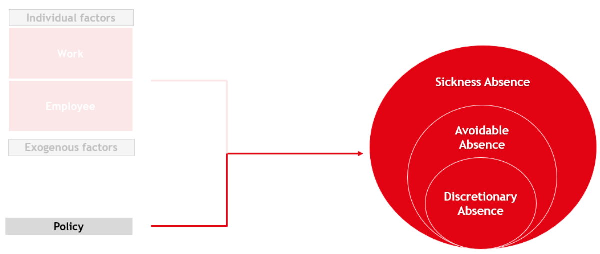

Figure 4: How does policy relate to sickness absence?

3.3.2 Regression determinant analysis

In addition to the exploratory policy analysis to answer SQ1, SQ2 uses an exploratory determinants analysis to examine how sickness absence varies across worker-profile characteristics, job and operational context, and exogenous conditions before estimating the regression models. The purpose of this step is not to test causal relationships, but to identify relevant empirical patterns, assess whether relationships appear linear or non-linear, and provide context for the interpretation of the OLS and survival models. The analysis mainly relies on sickness absence rate plots, because the absence rate is the main dependent variable in the OLS models and reflects the total absence burden relative to expected working time. Since the absence rate is shaped by both absence occurrence and spell duration, these plots also provide indirect insight into duration-related burden, although they do not separate frequency and duration directly.

Duration plots were produced where relevant, but only included in the analysis when they added substantive interpretive value. Duration plots that showed little variation, did not reveal meaningful group differences, or did not contribute to the interpretation of the regression models were excluded from the main analysis. The exploratory plots are structured around the same driver blocks as the regression models: employee characteristics, operational context, and exogenous factors. They help justify modelling choices such as role-specific models for Shoppers and Runners, categorical specifications for age, tenure, and commuting distance, and the inclusion of operational variables such as scheduling, shift type, performance, lateness, people per shift, and leadership absence. Like the policy analysis, this step remains interpretive rather than causal.

3.4 Ordinary Least Square Regression

SQ2 is addressed through regression analyses that relate sickness absence outcomes to employee-profile characteristics, job and operational context, and exogenous contextual factors. The aim is not to estimate causal effects of individual variables, but to identify which factors are consistently associated with sickness absence, whether these associations differ across countries and roles, and which patterns are most relevant for operational and policy interpretation. The regression strategy focuses on two outcomes: sickness absence rate and sickness spell duration. The absence-rate models examine the share of expected working time lost to sickness absence, first at the person-week level and then through a person-level aggregated OLS robustness model. Sickness spell duration is analysed using survival analysis in the subsequent section, which models return-to-work dynamics once a sickness spell has started. Together, these models provide a structured basis for assessing which individual and exogenous drivers are associated with the overall absence burden, which are related to absence persistence, and which findings are most relevant for operational response and broader policy reflection.

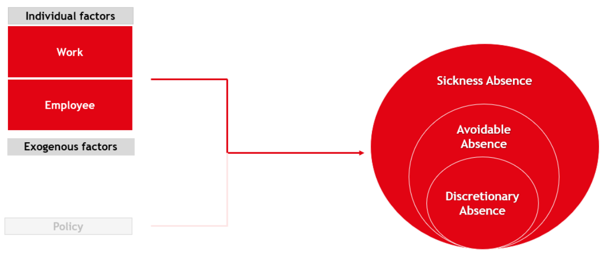

Figure 5: How do individual determinants relate to sicknes absence?

3.4.1 Sickness Absence rate OLS

Ordinary Least Squares regression is used to analyse the weekly sickness absence rate. OLS is a linear regression method that estimates the relationship between a dependent variable and a set of explanatory variables by choosing the coefficient values that minimise the sum of squared differences between the observed and predicted outcomes. The dependent variable is the weekly sickness absence rate, defined as the share of expected working time lost due to sickness absence in a given employee-week. The model therefore estimates how employee characteristics, operational context, and exogenous factors are associated with variation in the weekly absence burden, conditional on the other variables included in the model.

OLS is used because it directly matches the empirical purpose of SQ2: to assess to what extent sickness absence is associated with worker-profile characteristics, job and operational context, and exogenous factors across the Netherlands, Germany, and France. SQ2 is concerned with explaining variation in the overall absence burden, rather than only whether sickness absence occurs or how long a sickness spell lasts once it has started. The weekly sickness absence rate is therefore an appropriate dependent variable, because it measures the share of expected working time lost to sickness absence in each employee-week. Using OLS allows this absence burden to be related transparently to each variable of one of the explanatory blocks central to the research question, while holding the other included variables constant. This supports the comparative purpose of the thesis by making it possible to examine whether associations are similar or different across countries and roles. The standardized coefficients can also be interpreted directly, a one-standard-deviation increase in the explanatory variable is associated with a 0.01-standard-deviation increase in the weekly sickness absence rate, conditional on the other variables.

Several alternative model specifications were considered. Weighted OLS was not used as the main specification because the dependent variable is already normalised by expected working time: sickness absence hours are divided by expected hours. Additional weighting by expected hours would shift the model from an employee-week association towards an hours-weighted operational burden model, giving more influence to employees with larger contracts or more scheduled hours. This would be less aligned with SQ2, which focuses on associations between worker-profile, job-context and exogenous factors and sickness absence behaviour.

Zero-inflated models were also not selected. Although many employee-weeks have an absence rate of zero, these zeros are substantively meaningful observations of normal attendance, not necessarily “excess” zeros generated by a separate structural process. Zero-inflated models are mainly suited to count outcomes where part of the population is assumed to be structurally unable to experience the event (Lambert, 1992; Cameron & Trivedi, 2013). In this study, all included employees are in principle at risk of sickness absence.

Count models, such as Poisson or negative binomial regression, would be more suitable if the dependent variable were absence frequency, measured as the number of sickness spells or spell starts. However, as explained in Section 3.2, absence frequency is used descriptively rather than as a regression outcome because a clean frequency model would require comparable exposure or time-at-risk across employees. Employees differ in employment duration, contract size, scheduling intensity and observed exposure, meaning that a simple spell count would partly capture the opportunity to become absent rather than absence behaviour itself.

The OLS models are estimated separately for each country-role combination. This results in six main models: Shopper Netherlands, Shopper Germany, Shopper France, Runner Netherlands, Runner Germany, and Runner France. Estimating separate models allows the associations between sickness absence and the explanatory variables to differ across institutional and operational contexts, instead of imposing one pooled coefficient across all countries and roles.

The OLS specification improves comparability by applying the same absence-rate definition and conceptual driver blocks across countries and roles, while estimating separate country-role models to respect institutional and operational differences. However, the resulting coefficients should not be interpreted as pure cross-country policy effects, since country differences may also reflect workforce composition, operational maturity, local management practices, and differences in the meaning or distribution of specific variables. In addition, the model cannot include all factors that may influence sickness absence. Important determinants such as underlying health status, psychological well-being, household circumstances, and informal workplace dynamics are not fully observable in the available administrative and operational data. Therefore, omitted-variable bias cannot be fully avoided in this research, and the OLS' Zero conditional mean assumption is note met. The OLS results should consequently be interpreted as conditional associations based on the observed variables, rather than as complete explanations of sickness absence behaviour.

For each country (c) and role (r), the general person-week model can be in linear form written as:

$$\text{AbsenceRate}_{itr}^{(c,r)} = \beta_0^{(c,r)} + \beta_1^{(c,r)} X_{itr} + \beta_2^{(c,r)} Z_{it} + \beta_3^{(c,r)} C_i + \varepsilon_{it}^{(c,r)} \tag{8}$$

where $\text{AbsenceRate}_{itr}^{(c,r)}$ is the sickness absence rate of employee i in week t for role r, estimated separately for country-role combination (c, r). The index i denotes the employee, t denotes the calendar week, r denotes the role, either Shopper or Runner, and c denotes the country, either the Netherlands, Germany, or France. X_{itr} represents the employee-characteristics block, including contract type, tenure, age, gender, and distance to work. Z_{it} represents the operational-context block, measured over the preceding four-week period, including scheduling, shift timing, lateness, people per shift, lead or Captain absence, colleague absence, and role-specific performance. C_i represents the exogenous-context block, including national influenza level, economic growth, and major operational disruptions. $\beta_0^{(c,r)}$ is the intercept for each country-role model, $\beta_1^{(c,r)}$, $\beta_2^{(c,r)}$, and $\beta_3^{(c,r)}$ are the estimated coefficient vectors for the corresponding variable blocks, and $\varepsilon_{it}^{(c,r)}$ is the error term.

The dependent variable in the model, the weekly sickness absence rate, ranges from 0 to 1, where 0 indicates no sickness absence in the employee-week and 1 indicates that all expected working time in that week was lost due to sickness absence. The independent variables are operationalized in line with the definitions described in Section 3.2 and Appendix A.

Categorical variables are included as dummy variables. To avoid breaking OLS; perfect multicollinearity assumption, one category is omitted from each set of categorical variables and treated as the reference category. The reference categories are chosen to provide a meaningful operational baseline and are reported with the corresponding regression tables. This applies to contract type, tenure, age, distance-to-work, weekday composition, shift-time composition, and shift-type composition where applicable. Because of this exclusion, variables will also not perfectly align with the lagged number of shifts.

Continuous explanatory variables are standardised within the relevant estimation sample before model estimation. This means that each continuous variable is transformed by subtracting its sample mean and dividing by its sample standard deviation. This improves comparability between coefficients that are measured on different scales. Dummy variables remain interpretable relative to their omitted reference category.

Because the same employee can appear in multiple employee-weeks, observations are not fully independent within individuals, and thus not homoskedastic. In the main OLS specification, standard errors are therefore estimated using HC3 heteroskedasticity-robust standard errors. This makes the inference less sensitive to non-constant error variance across observations. However, HC3 standard errors do not remove the repeated-observation structure itself, nor do they fully account for within-employee dependence across weeks. Therefore, the next section implements a person-level robustness OLS model, in which each employee appears only once. This robustness model is used to assess whether the main associations remain comparable when the repeated person-week structure is removed. The estimated coefficients are interpreted as conditional associations with the weekly sickness absence rate, rather than as causal effects.

3.4.2 Robustness OLS

To assess whether the main absence-rate findings are robust to the repeated person-week structure, an additional OLS model is estimated on a person-level aggregated dataset. In this model, each employee appears only once per aggregation period. The dependent variable is the person-level sickness absence rate, calculated as total sickness absence hours divided by total expected working hours over the observed period, following Equation 1 in Section 3.2. The operationalization of the person-level robustness model follows the previous sections general model, the independent variable operationalization is described in section 3.2. and Appendix A. The model is still an ordinary least squares regression, but the unit of analysis changes from the employee-week to the employee. It therefore estimates how differences between employees in average profile characteristics, average operational exposure, and average exogenous context are associated with their overall sickness absence rate during the observation period. The coefficients are interpreted as conditional associations with the person-level sickness absence rate, similair to the employee-week model.

The purpose of this model is not to replace the person-week OLS analysis, but to test whether the main associations are sensitive to the repeated weekly structure of the data. The person-week model preserves short-term variation and is therefore better suited to analysing recent operational conditions. However, because the same employee can appear in multiple weeks, the results may partly reflect within-person repetition. The person-level robustness model removes this repeated-observation structure by collapsing the data to one observation per employee. If the main associations remain similar in direction and substantive interpretation, this strengthens confidence that the findings are not only driven by repeated weekly observations from the same individuals.

Alternative approaches were considered but are less aligned with the purpose of this robustness check. Clustered or heteroskedasticity-robust standard errors adjust inference in the main person-week model, but they do not remove the repeated-observation structure itself. Fixed-effects models would control for time-invariant employee characteristics, but would also absorb important between-person variables that are central to this thesis, such as gender, distance to work, contract structure, and much of the variation in age and tenure.

The robustness model has clear interpretation boundaries. By aggregating the data to the employee level, the model sacrifices week-level variation and is less suitable for analysing short-term operational exposure or temporary shocks. In addition, averaging time-varying variables may reduce variation between observations, because temporary peaks and troughs in scheduling, lateness, performance, team context, or exogenous exposure are smoothed into employee-level averages. This can make employees appear more similar than they are in the weekly data and may reduce the ability of the OLS model to identify associations that depend on short-term variation. The robustness model should therefore be interpreted as a check of whether broad employee-level patterns remain visible, not as a more precise substitute for the person-week model. It should also not be used as the primary basis for direct cross-country comparison. Aggregating the data changes the variation available to the model and may affect countries and roles differently, especially when they differ in observation length, workforce turnover, contract structure, or the amount of variation in operational variables. As a result, differences in the robustness coefficients may partly reflect the aggregation procedure itself rather than substantive cross-country differences in sickness absence behaviour. In addition, the model remains associative rather than causal. Unobserved factors such as underlying health, psychological well-being, household circumstances, or informal workplace dynamics cannot be fully captured in the available administrative and operational data. Omitted-variable bias can therefore not be fully avoided.

3.5 Survival analysis

Survival analysis is used to analyse the duration of sickness absence spells. Survival analysis is a time-to-event method that estimates how long it takes until a defined event occurs. The unit of analysis is the individual sickness absence spell, and the event of interest is the end of the sickness absence spell, interpreted as return-to-work. The dependent variable is therefore the duration of a sickness absence spell, measured in calendar days from the recorded start date of the spell until the recorded end date.

The central quantity in survival analysis is the hazard rate. In this thesis, the hazard rate represents the instantaneous return-to-work rate at a given spell duration, conditional on the employee still being absent just before that moment. In other words, the model does not only ask whether a sickness spell eventually ends, but estimates how the likelihood of returning to work changes over the course of the spell. This makes survival analysis suitable for sickness absence duration, because the timing of return-to-work is substantively important and not all spells necessarily end within the observation period. The multivariate Cox proportional hazards model extends this logic by estimating how several explanatory variables are associated with the return-to-work rate simultaneously. The model compares the hazard of return-to-work between employees or spells with different characteristics, while holding the other included variables constant. The estimated coefficients are reported as hazard ratios. A hazard ratio above 1 indicates a higher return-to-work rate and therefore shorter expected sickness spells, while a hazard ratio below 1 indicates a longer expected sickness spells. The model therefore estimates how employee characteristics, operational context, and exogenous factors are associated with absence duration, conditional on the other variables included in the model.

Several alternative duration models were considered. OLS regression on spell length was considered, but was not selected as the main duration model. The main limitation is that OLS treats spell duration as a completed continuous outcome and estimates average differences in total spell length. This would show whether certain employee or operational characteristics are associated with longer or shorter spells on average, but it would not model the return-to-work process itself. The Cox proportional hazards model is more suitable because it estimates the hazard that a sickness spell ends at a given duration, conditional on the employee still being absent just before that point. In other words, it analyses the rate of return-to-work over spell duration, rather than only the final number of days absent.

A frailty model was also considered as an extension of the Cox proportional hazards model. Frailty models include an additional random effect to account for unobserved heterogeneity between clusters, such as employees, teams, locations, or countries.Such a specification is conceptually relevant in this study, because it is acknowledged that sickness absence duration is likely to be influenced by unobserved employee-, team-, or site-level characteristics that cannot be fully captured in the available administrative and operational data. However, a frailty model was not selected as the main specification because the purpose of this thesis is to estimate transparent associations between observed driver blocks and sickness spell duration across country-role groups. Introducing frailty terms would shift part of the explanation to latent, unobserved heterogeneity, making the estimated associations less straightforward to interpret and compare across the six country-role models. In addition, the number of spells, repeated spells, and potential clustering structures differ across countries and roles, which would make the frailty specification less consistent across models. The standard Cox proportional hazards model was therefore retained as the main duration model, while the results are interpreted cautiously because unobserved employee-, team-, or site-level factors may still influence spell duration.

The multivariate Cox proportional hazard models are estimated separately for each country-role combination. This results in six main models: Shopper Netherlands, Shopper Germany, Shopper France, Runner Netherlands, Runner Germany, and Runner France. Estimating separate models allows the associations between spell duration and the explanatory variables to differ across institutional and operational contexts, instead of imposing one pooled coefficient across all countries and roles. The model includes all observed completed spell lengths per specification. Separate models for short-, medium-, and long-duration spells were not estimated, because splitting the data by duration would substantially reduce the number of observations within each country-role group and weaken the statistical power of the analysis.

For each country (c) and role (r), the general person-week model can be written as:

$$h_j^{(c,r)}(t) = h_0^{(c,r)}(t) \exp\left(\beta_1^{(c,r)} X_{ijr} + \beta_2^{(c,r)} Z_{i,t-1,r} + \beta_3^{(c,r)} C_{ct}\right) \tag{9}$$

where $h_j^{(c,r)}(t)$ is the hazard rate of return-to-work for sickness absence spell j at spell duration t, estimated separately for country-role combination (c, r). The index j denotes the sickness absence spell, i denotes the employee, t denotes the duration time within the spell, r denotes the role, either Shopper or Runner, and c denotes the country, either the Netherlands, Germany, or France. $h_0^{(c,r)}(t)$ is the baseline hazard for each country-role model and captures how the underlying return-to-work rate changes over spell duration when the covariates are at their reference or baseline values. X_{ijr} represents the employee-characteristics block, including contract type, tenure, age, gender, and distance to work. $Z_{i,t-1,r}$ represents the operational-context block, measured over the four weeks preceding the start of the sickness absence spell, including scheduling, shift timing, lateness, people per shift, lead or Captain absence, colleague absence, and role-specific performance. For Shoppers, this block also includes shift-type variables by temperature zone. C_{ct} represents the exogenous-context block, including national influenza level, economic growth, and major operational disruptions. $\beta_1^{(c,r)}$, $\beta_2^{(c,r)}$, and $\beta_3^{(c,r)}$ are the estimated coefficient vectors for the corresponding variable blocks.

The dependent variable in the model, the spell duration, ranges from 1 to n, indicating the number of days the sickness absence spell lasted. The independent variables are operationalised in line with the definitions described in Section 3.2 and Appendix A.

Categorical variables are included as dummy variables. To avoid multicollinearity, one category is omitted from each set of categorical variables and treated as the reference category. This applies to contract type, tenure, age, distance-to-work, weekday composition, shift-time composition, and shift-type composition where applicable. The reference categories are chosen to provide a meaningful operational baseline and are reported with the corresponding regression tables.

Continuous explanatory variables are standardised within each country-role estimation sample before estimating the Cox model. The reported hazard ratios for these variables therefore represent the association with a one-standard-deviation increase in the explanatory variable, holding the other variables constant. Dummy variables are not standardised and remain interpretable relative to their omitted reference category.

The main assumption of the Cox proportional hazards model is that the hazard ratios are proportional over spell duration. This means that the relative association between an explanatory variable and the return-to-work hazard is assumed to remain constant over time. In practice, this may be a restrictive assumption, because some variables may affect short sickness spells differently from medium- or long-duration spells. If proportionality does not hold, an estimated hazard ratio is more appropriately interpreted as an overall, time-aggregated association than as an association that necessarily applies equally throughout the spell. This overall estimate nevertheless remains informative for the comparative purpose of the analysis. Cross-country differences in hazard ratios should however be interpreted cautiously as comparative associations, not as causal evidence, results may also reflect differences in unobserved return-to-work determinants.

Before estimating the multivariate Cox proportional hazards models, Kaplan-Meier survival curves are used as a descriptive survival-analysis tool. The purpose of these curves is to visualise how sickness absence spells end over time across countries and roles. In this thesis, the Kaplan-Meier curve represents the estimated probability that an employee remains absent beyond a given spell duration. Since the event of interest is return-to-work, a steeper decline in the curve indicates that sickness spells end more quickly, while a flatter curve indicates more persistent sickness absence.

3.6 Operational and Policy strategy foundation

Figure 7 shows the synthesis logic used to answer SQ3. To answer this question, the section combines the two empirical streams from regression analysis. The OLS models show where the overall weekly absence burden concentrates per role and country, while the survival models clarify whether these patterns are more related to short-term absence or to longer return-to-work dynamics. SQ3 therefore does not introduce a new statistical model, but translates the previous empirical findings into an operational and policy evidence base.

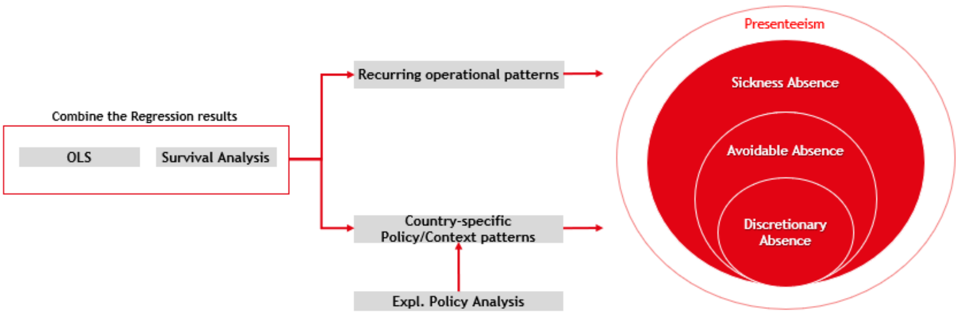

Figure 6: SQ3 methodological framework

The synthesis first separates the regression findings into recurring operational patterns and country-specific policy or context patterns. Recurring operational patterns are findings that appear across countries, roles, or models and are therefore most relevant for logistics' internal strategy. Country-specific patterns are findings whose meaning differs between the Netherlands, Germany, and France. These are interpreted with support from the exploratory policy analysis, which identifies which national institutional levers are expected to matter at specific absence margins. Finally, both types of findings are connected to the absence-type framework. This makes it possible to assess whether the evidence points mainly toward legitimate recovery absence, work-related avoidable absence, discretionary or threshold-sensitive absence, or presenteeism risk, without classifying individual sickness cases directly. This distinction allows the recommendations to be targeted more precisely at the relevant absence margin, rather than treating sickness absence as one uniform problem.

4 Results

4.1 Exploratory Analyses

4.1.1 Exploratory Policy analysis

Below a written summary of each Social Security Framework that is used in the empirical assessment can be found. More detailed tables on the frameworks can be found in Appendix B.

Netherlands

In the Dutch context, Picnic's implementation of sickness absence follows the statutory framework of employer wage continuation during illness, combined with provisions from the E-commerce CAO. A first relevant element is the use of waiting days. Under the E-commerce CAO, between 0 and 2 waiting days may apply at the start of a sickness absence spell. However, if an employee has not been sick in the previous 6 months, no waiting days are applied. In practice, this means that the financial effect of reporting sick depends partly on recent sickness history.

A second important element is the replacement-rate schedule over time, which determines how much of the wage is paid during a sickness absence spell and for how long the employer remains responsible. In Picnic's implementation, the employer bears the wage costs during the first 104 weeks of sickness absence, after which the employee may enter the WIA scheme. The replacement schedule is applied as follows. For day 3 to day 28, wage continuation is set at 70% of the minimum wage, paid by the employer. In practice, however, this works out to an effective replacement rate of 92.76% of the Picnic hourly wage used in 2024–2025, because the wage level at Picnic has grown alongside the Dutch minimum wage. Using the 2024–2025 reference values, 92.76% of a gross hourly wage of €15.96 equals €14.81, which corresponds to the minimum wage level.

This effective replacement rate requires some clarification. The correction for minimum wage protection applies at the level of the monthly wage, not necessarily at the level of a single day. This means that for a very short sickness absence, such as one day, a worker may in practice receive only 70% for that day, without immediately falling below the monthly minimum wage threshold. However, once the sickness absence lasts longer, approximately from around two weeks onward, a 70% payment rate would reduce the monthly wage sufficiently for the minimum wage correction to become binding. From that point onward, the payment effectively cannot fall below approximately 92.76% of the Picnic wage.

After the first four weeks, the E-commerce CAO provides a more generous continuation schedule. From week 4 to week 52, the employer pays 85% of wage, although the effective payment remains at least 92.76% where the minimum wage floor binds. From week 52 to week 78, the employer continues to pay 85%. From week 79 to week 104, payment falls back to 70%, still borne by the employer. After this 104-week period, responsibility shifts to the public disability scheme (WIA).

Another important feature of the Dutch implementation concerns the treatment of recurrent sickness absence. If a worker recovers and becomes sick again within 4 weeks, the new sickness spell is treated as a continuation of the previous spell. For the purpose of determining total sickness duration, the intervening period of recovery is therefore not counted as a reset, but the sickness periods are linked together. Apart from this 4-week linking rule, duration is measured using ordinary calendar days.

Finally, with regard to eligibility and certification requirements, Picnic's implementation does not include additional formal requirements such as a doctor's note. In that sense, there are no separate certification barriers imposed at the start of a sickness absence spell.

Absence Expectations: Following the propositions on wage replacement rates, waiting days, and doctor's note requirements stated in conclusions and implications section of the literature review in Chapter 2, and based on the Dutch social security framework, the Dutch system is expected to produce two main duration-specific absence patterns. First, short-term sickness reporting is expected to be relatively high, because Picnic's Dutch implementation does not require a doctor's note and the waiting-day rule is conditional. Employees without sickness absence in the previous six months face zero waiting days, while recurrent sickness absence can face two waiting days. As a result, the administrative threshold for reporting sick is low, while the financial threshold only applies to part of the workforce. Second, medium- and long-term absence continuation is expected to be relatively persistent because the effective WRR remains high for a long period. Although the nominal WRR is 70% from day 3 to day 28, the minimum-wage floor can raise the effective replacement rate to approximately 92.76% for longer spells. From week 4 to week 52, WRR is 85%, again with an effective lower bound where the minimum-wage floor binds, and from week 52 to week 78 the WRR remains 85%. Only from week 79 to week 104 does the replacement rate fall back to 70%. Therefore, the Dutch framework is expected to be associated with relatively high very short-term sickness reporting and relatively high long-term absence persistence.

Germany

In the German context, Picnic's implementation of sickness absence follows the statutory logic of continued remuneration during illness (Entgeltfortzahlung) and subsequent sickness benefit (Krankengeld) through the statutory health insurance system. Unlike the Dutch arrangement, the German framework does not use waiting days. Once an employee reports sick, the general rule is that the employer continues paying full remuneration for up to six weeks, that is, 42 calendar days. A relevant exception applies during the first four weeks of a new employment relationship: in that initial period, the employee is generally not yet entitled to employer-paid continued remuneration, and sickness benefit is instead paid by the health insurer.

A second important element is the replacement-rate schedule over time. For day 1 to day 42, the employer bears the wage costs and pays 100% of wage. From day 43 onward, Picnic's framework moves to statutory sickness benefit paid by the insurer. Under German rules, this benefit amounts to 70% of gross pay, capped at 90% of net pay. It can be paid for a maximum of 78 weeks within a 3-year period for the same illness. This means that long-term income protection shifts away from the employer after the first six weeks and also becomes less generous.

Certification requirements are another relevant feature. In the general German framework, a medical certificate is typically required from the fourth calendar day of illness, but employers are allowed to demand it earlier. Picnic uses that room for a stricter internal differentiation: Shoppers and Runners are required to provide a doctor's note from the first day of absence, whereas Captains and other Leads are required to do so from the third day. In practice, this fits the German electronic certification system, in which the doctor transmits the certificate of incapacity for work digitally to the health insurer and the employer retrieves it electronically.

Another important feature concerns the treatment of recurrent sickness absence. If a worker recovers and later becomes sick again due to a different illness or injury, the new sickness spell starts again from day 0. At the same time, it is worth noting that German law does not allow an unlimited reset for the same illness. Statutory sickness benefit remains limited to 78 weeks within 3 years for the same condition. After that point, entitlement does not simply continue as ordinary sickness pay. Instead, the employee is typically referred onward for further assessment, for example through the Federal Employment Agency or the pension insurance system, depending on remaining work capacity and whether rehabilitation or disability pension becomes relevant.

Absence Expectations: Following the same propositions from Chapter 2, and based on the German social security framework described in Chapter 3.4 and Appendix B, the German system is expected to produce high short- and medium-term absence, but lower long-term absence persistence. The key reason is that Germany combines zero waiting days with 100% WRR from day 1 to day 42. This means that employees face no direct income loss when reporting sick or when remaining absent during the first six weeks. Therefore, absence is expected to be relatively high throughout the fully compensated period, especially between the first few days and day 42. However, Picnic's German implementation requires Shoppers and Runners to provide a doctor's note from day 1, which raises the administrative threshold for very short sickness reporting. This means that one-day absence may be somewhat discouraged, even though the financial incentive remains generous. After day 42, WRR falls to statutory sickness benefit of approximately 70% of gross pay, capped at 90% of net pay. From that point onward, the financial cost of continued absence increases. Therefore, German absence is expected to concentrate mainly in the fully compensated 1–42 day period, with lower continuation into medium-long and long-term absence once WRR falls.

France

In the French context, Picnic's sickness absence implementation combines the statutory French sickness-benefit system with employer salary-maintenance provisions specified in Picnic's French payroll/CAO blueprint. The statutory system includes a waiting period before daily sickness benefits are paid. In general, sickness benefits start after three waiting days, meaning that the first three calendar days of ordinary sickness absence are unpaid by the social-security system.

A second important element is the replacement-rate schedule over time. From day 4 onward, the employee may receive statutory daily sickness benefits, roughly equal to 50% of the reference wage.

In addition, Picnic's French implementation provides an employer top-up, but the generosity and duration of this top-up depend on the legal entity, employee category, and seniority.

For Picnic's operational population, the clearest distinction is between Shoppers and Runner, and Captains and Leads. For Shoppers and Runners, employer-maintained compensation starts only from the 6th day of sickness absence, provided the employee has

at least 36 months of seniority. Depending on seniority, compensation is maintained at 100for an initial period and then at 75% for a second period. For employees with 36–60 months of seniority, this means 100% from day 6 to day 40 and 75% from day 41 to day 70. With higher seniority, these periods become longer.

For Captains and Leads, the employer top-up starts earlier, from the 1st day of sickness absence, again conditional on seniority. Captains receive 100% for an initial period and 75% afterward, with the length of both periods increasing with seniority. Leads receive a more generous duration than Captains, especially for long spells.

Certification requirements are stricter than in the Netherlands. Under Picnic's French implementation, Shoppers and Runners are required to provide a doctor's note from the first day of absence and within 48 hours. Captains and other Leads are required to provide a doctor's note from the third day of absence.

Finally, regarding recurrent sickness absence, the French implementation can be treated similarly to Germany for the purpose of the analysis: if the worker recovers and later becomes sick again due to a different illness or injury, the absence count starts again from zero. For the same or related illness, benefit entitlement is limited by the maximum statutory sickness-benefit duration, commonly 360 daily benefits over a period of up to three years.

Absence Expectations: Following the propositions from Chapter 2, and based on the French social security framework described in Chapter 3.4 and Appendix B, the French system is expected to discourage very short-term sickness reporting, while creating more differentiated absence expectations later in the spell depending on tenure. In the first three days, employees face both a doctor's note requirement from day 1 and three waiting days. This means that very short sickness absence involves both an administrative burden and no statutory wage replacement, so short-term absence is expected to be relatively low. From day 4 to day 5, statutory sickness benefit starts, but the effective WRR is only around 50%, because employer top-up for Shoppers and Runners starts only from day 6 and only for employees with sufficient seniority. For employees with less than 36 months of seniority, WRR therefore remains relatively low, so absence continuation is expected to be less financially attractive than in Germany or the Netherlands. For employees with at least 36 months of seniority, however, the effective WRR can rise to 100% during the first top-up period and then fall to 75% in the second top-up period. For example, employees with 36–60 months of seniority receive 100% WRR from day 6 to day 40 and 75% from day 41 to day 70, while higher-tenure employees receive these top-ups for longer. Therefore, the French framework is expected to produce low very short-term absence, moderate absence under the basic statutory 50% regime, and higher medium-duration absence mainly among employees eligible for tenure-based employer top-ups.

Plots and further specific explanation of the analysis have been placed in Confidential Annex J, and can not be shown in this version due to company-sensitive data.

4.1.2 Exploratory individual determinants analysis

After comparing the national policy frameworks and the expected absence margins of the propositions, the exploratory analysis shifts to variation within logistics' workforce. This step is necessary because cross-country policy differences alone cannot explain observed sickness absence patterns. Even within the same national regime, absence may differ by role, location, contract type, age, tenure, gender, commuting distance, and operational context. These exploratory plots therefore provide the bridge between the policy analysis and the multivariate regression models. Plots and further specific explanation have been placed in Confidential Annex J, and can not be shown in this version due to company-sensitive data.

4.1.3 Results synthesis

The policy analysis broadly supports the propositions developed in the literature review and suggests that national sickness absence frameworks are most informative when interpreted at specific absence margins rather than as general explanations for higher or lower absence.

The Dutch pattern points to two different policy-sensitive margins. First, the high concentration of one-day absence is consistent with a relatively low short-term reporting threshold, since there is no formal doctor's note requirement and waiting days apply only conditionally. Second, the relatively high long-term absence burden is consistent with the extended Dutch wage-continuation framework, in which employer responsibility and relatively high effective income protection remain in place for a long period. However, the relatively low medium-term absence suggests that Dutch absence cannot be explained by generosity alone. The Dutch framework therefore appears most relevant at the very short-term onset margin and at the long-term persistence margin, rather than across the full duration distribution.

The German pattern suggests a different policy mechanism. The relatively limited one-day absence is consistent with the day-one doctor's note requirement for Shoppers and Runners, indicating that certification may raise the administrative threshold for the shortest spells. At the same time, the absence of waiting days and 100% wage replacement during the first 42 days are consistent with the high short- and medium-duration absence burden. This suggests that certification alone may reduce some very short-term reporting, but does not fully offset the effect of generous early-stage sick pay. The lower long-term absence after the first six weeks is consistent with the drop in wage replacement after day 42.

The French pattern provides the clearest evidence for the short-term effect of stricter reporting barriers. France combines three waiting days with a doctor's note requirement from the first day, and it shows relatively low very short-term absence and low absence frequency. This supports the interpretation that financial and administrative barriers can raise the short-term absence threshold. However, the relatively high absence volume in the 42-182 day range is not well explained by the baseline French wage replacement rate, and the tenure-based employer top-up applies to only a limited part of the operational workforce. This suggests that French medium-duration absence is more likely related to other mechanisms, such as health severity, workforce composition, role-specific working conditions, recurrence among a smaller group of workers, or location-level factors.

The exploratory determinants analysis shows that sickness absence varies substantially within countries, indicating that national policy cannot be the only relevant explanation. Role differences are especially important: Shoppers show a stronger concentration of short-term absence, whereas Runners display relatively more medium- and long-duration absence. This suggests that the two roles may be associated with different absence mechanisms, this can be validated in survival analysis. The observed variation between fulfilment centres and hubs further supports this interpretation. If national policy were the dominant explanation, absence patterns would be expected to be more homogeneous within countries. Instead, the location-level variation suggests that operational conditions may explain part of the remaining absence variation, this will be investigated in the OLS Regression.

The employee-profile patterns show that contract type, age, tenure, gender, and commuting distance should be included in the regression models, but interpreted as compositional indicators rather than direct causal mechanisms. Contract type is relevant because permanent and fixed-term employees display different absence patterns, although this relationship may also capture tenure, age, job attachment, selection, health differences, or employment security. Age and tenure also show non-linear relationships with sickness absence: older employees may have longer spell durations, while younger or early-tenure employees may show higher absence rates or more frequent short spells. This justifies treating age and tenure categorically. Commuting distance may add explanatory value, but should be interpreted cautiously because it may capture commuting burden as well as transport mode, urban labour-market composition, student populations, or site-specific recruitment areas.

The operational context is likely to matter, but also as a proxy for broader operational conditions. Performance, lateness, team absence, lead absence, staffing context, and scheduling variables may reflect work routines, motivation and employee selection. These variables should therefore be included in the regression models to account for operational context, but their coefficients should not be interpreted as direct causal effects. This is especially important for scheduling variables. Weekend work, shift timing, and shift type appear particularly relevant for Shoppers, while Runner absence is more stable across weekdays and shift times. These patterns suggest that scheduling variables also capture meaningful job-context variation.

4.2 Ordinary Least Squares Regression

Before presenting the regression results, it is important to note that the relevant reference categories are stated above each analysis. To reduce multicollinearity, selected variables were grouped or chosen as reference after assessing the descriptive statistics tables in Appendix I, the

OLS correlation matrix in Appendix H and early runs of the models in the scheduling variables. Monday to Thursday shifts were combined, weekend days were combined, and evening and night shifts were combined. Only the Total shifts variable was never excluded from the model, eventhough high VIF values were found. Without this variable, scheduling variables are not controlled for the amount of worked shitfs and loose their interpretability. Total shifts and its strongly correlated variables should not be interpreted while having a high VIF. The coefficients should be interpreted relative to these grouped reference or comparison categories as specified in each model. The main results can be found in tables in this section, the corresponding VIF-diagnostics can be found in Appendix H.

4.2.1 Sickness Absence rate OLS

Shoppers

Table 2: Shopper absence-rate OLS models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Walking distance; Monday–Thursday shifts; Afternoon shifts; Ambient shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Permanent contract	0.039***		-0.053***
Female	0.033***	0.038***	0.005*
Age 26–40	0.009†	0.024***	-0.062***
Age 40+	0.023***	0.028***	-0.058***
Tenure 94–187 days	0.000	0.136***	-0.007**
Tenure 188–365 days	-0.009	0.149***	0.008**
Tenure 366–730 days	-0.021	0.142***	-0.024***
Tenure 731–1095 days	-0.020	0.031***	0.005†
Tenure 1096–1460 days	-0.010	-0.003	-0.000
Tenure 1461+ days	0.062***	-0.001	0.015***
Distance			
Biking distance	0.023***	-0.093***	-0.007*
Driving distance	0.023***	-0.084***	-0.015***
Scheduling: total volume			
Total shifts in previous 4 weeks	-0.094***	0.201***	0.133***
Scheduling: weekday composition			
Monday shifts	-0.040***	-0.016†	-0.011***
Friday shifts	0.023***	-0.027**	-0.009**
Weekend shifts	-0.034***	-0.020**	-0.010***
Scheduling: shift time			
Morning shifts	-0.005	-0.048***	0.007*
Evening/night shifts	-0.023***	-0.007***	-0.011***
Scheduling: shift type			
Chilled shifts	-0.065***	-0.357***	-0.183***
Frozen shifts	-0.025***	-0.087***	-0.037***
Operational and performance context			
People per shift	-0.131***	-0.029***	0.037***
Picking/replenishment speed	-0.006*	0.085***	0.014***
Late shifts	-0.022***	-0.051***	-0.008***
Leadership/team context			
Captain absence rate	-0.013***	0.024***	0.041***

Exogenous controls			
Influenza level	0.019***	-0.032***	-0.007**
Economic growth	0.011**	-0.078***	0.031***
Major operational disruptions	-0.006†	0.005	-0.003
Model fit			
Adjusted R^2	0.109	0.153	0.043

Notes: Coefficients are standardized OLS estimates. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model because of too little variance.

The Shopper OLS models show that absence-rate associations differ substantially across countries. Model fit was highest in France (adj.R^2=.153), followed by the Netherlands (.109) and Germany (.043). This suggests that the included employee-profile, scheduling, operational, and exogenous variables explain the largest share of Runner absence-rate variation in France. The lower explanatory power in Germany may partly reflect the larger or a more heterogeneous German dataset, where more observations and operational variation create more variance to explain. As with the Shopper models, the large sample size also increases statistical power, meaning that coefficients may become statistically significant even when their substantive effect is limited. Therefore, significance should be interpreted together with coefficient size, sign plausibility, VIF diagnostics, and robustness. This mechanism is applicable to every model in this Chapter.

The Shopper OLS results show that employee-profile associations are strongly country-specific rather than uniform across logistics operations. Permanent contracts are positively associated with Shopper absence in the Netherlands (β = .039), but negatively associated with Shopper absence in Germany(-.053). Because age and tenure are already controlled for in the model, this opposite sign cannot be explained by permanent employees being older or more tenured. Instead, contract type appears to capture a different country-specific mechanism, potentially related to employment security, contract allocation, worker selection, job attachment, or local HR practices. The coefficient should therefore be interpreted as a conditional association with the meaning of permanent employment within each country, rather than as a universal contract-security effect.

Female Shoppers are positively associated with absence in all three countries, making gender one of the more consistent employee-profile findings in the Shopper models. Age however differs by country: older age groups are associated with higher absence in the Netherlands (β = .023) and France (.028), but lower absence in Germany (-.058). These contrasting patterns suggest that age captures country-specific differences in workforce composition and sickness-absence behaviour. In France, the positive tenure association is particularly notable because it suggests that absence may be concentrated among employees who remain in the organisation for longer. This could indicate selective retention: employees with lower absence propensity, or better outside opportunities may leave earlier, while employees with higher absence propensity remain in the workforce. Tenure may therefore capture difficulties in talent retention in France.

Commuting distance does not show one consistent mechanism across countries. Longer commuting-distance categories are associated with higher absence in the Netherlands, but lower absence in France and Germany. This suggests that commuting distance should be treated as a contextual employee-profile indicator rather than as direct evidence of commuting burden. It may also capture urban density, public-transport availability, local labour-market composition or site-specific recruitment patterns.

The scheduling block suggests that Shopper absence is related to when and where work is scheduled, although some coefficients should be interpreted cautiously. The number of shifts mainly controls for recent work exposure and has high VIF values, so it should not be read as a clean independent effect. The weekday pattern is most notable in the Netherlands, where Friday shifts are significantly associated with higher absence ($\beta = .023$). This may reflect leisure-related timing effects, especially in a setting with no formal doctor's note requirement and only conditional waiting days, although this remains an associative interpretation. Weekend shifts are generally associated with lower Shopper absence, possibly because weekend work is concentrated among employees with different availability patterns or because more free time during the regular working week supports recovery and work planning. The clearest scheduling-related result is that Chilled and Frozen shifts are consistently associated with lower absence than Ambient shifts.

The operational and team-context variables show that absence is partly related to local operational conditions, but not through one uniform mechanism. People per shift and picking/replenishment speed have mixed signs across countries, suggesting that they capture different local meanings and might not capture the true relationship well. Late shifts, however, are consistently negatively associated with absence across the Shopper models, which likely reflects motivation. Captain absence rate is positively associated with Shopper absence in France and Germany, but negatively in the Netherlands, indicating that team context may matter differently per country and location.

The exogenous controls are statistically relevant, but their inconsistent signs suggest that they mainly capture country-specific timing and contextual variation rather than one general external mechanism. Their average levels also differed across countries in the descriptive statistics, reinforcing the interpretation that these variables reflect distinct national contexts. The Robustness OLS might shed clarity on this validity. Major operational disruptions explain relatively little variation and are not a central finding for Shoppers. The German model has the lowest fit, which may reflect the larger German workforce in this operational setting.

Runners

Table 3: Runner absence-rate OLS models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Walking distance; Monday–Thursday shifts; Afternoon shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Permanent contract	-0.007		0.013***
Female	0.040***	0.062***	0.018***
Age 26–40	0.084***	0.024***	0.004*
Age 40+	0.123***	0.015*	-0.010***
Tenure 94–187 days	0.004	0.113***	0.044***
Tenure 188–365 days	0.024***	0.186***	0.046***
Tenure 366–730 days	0.029**	0.088***	0.027***
Tenure 731–1095 days	0.038**	0.049***	-0.008**
Tenure 1096–1460 days	0.085***	0.051***	-0.001
Tenure 1461+ days	0.067***	0.034***	-0.002
Distance			
Biking distance	0.004	-0.063***	0.012***
Driving distance	0.003	-0.034***	0.013***
Scheduling: total volume			
Total shifts in previous 4 weeks	-0.003	-0.178***	-0.029***
Scheduling: weekday composition			
Monday shifts	-0.028***	0.046***	0.035***
Friday shifts	-0.038***	0.001	-0.032***
Weekend shifts	-0.102***	-0.094***	-0.066***
Scheduling: shift time			
Morning shifts	-0.131***	-0.013*	-0.034***
Evening/night shifts	-0.142***	-0.025	-0.093***
Operational and performance context			
Driving score			-0.014***
Late shifts	0.007*	-0.053***	0.005**
Leadership/team context			
Captain absence rate	0.021***	0.022***	0.004*
Exogenous controls			
Influenza level	0.004	0.020***	0.022***
Economic growth	-0.011*	-0.010*	-0.003
Major operational disruptions	-0.001	0.012*	-0.006***
Model fit			
Adjusted R^2	0.082	0.113	0.031

Notes: Coefficients are standardized OLS estimates. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model because of too little variance.

The Runner OLS estimates are presented in Table 8. Model fit was highest in France (adj. R^2 = .113), followed by the Netherlands (.082) and Germany (.031). For the employee-profile variables in the Runner OLS model, Permanent-contract status was not significantly associated with Runner absence in the Netherlands, but showed a small positive association in Germany (β = .013). Female Runners have higher absence rates in all three countries, making gender also one of the more consistent profile-related findings in the Runner models. Age is also significant across countries, but the direction differs: older Runners are associated with higher absence in the Netherlands (β = .123) and France (β = .062), while older German Runners show slightly lower absence (β = -.010). A more probable explanation is a higher absence of the reference category, the 26- employees. The subsequent survival analysis might give more context to type term of this absence, and the root of the relationship.

Tenure was generally positively associated with Runner absence in the Netherlands and France. In France, all included tenure categories had positive coefficients, with the largest estimate found for employees with 188–365 days of tenure (β = .186). The German pattern was more clearly non-linear: tenure coefficients were positive up to 730 days, but small, negative, or non-significant among longer-tenured groups. Because age is already controlled for, this relationship should not be interpreted simply as older workers being more often absent. Instead, tenure may capture mechanisms specific to employees who have remained in the Runner role for longer. Dutch and espescially French longer-tenured employees may feel less constrained or less hesitant to report sick, because they are more familiar with the organisation, absence procedures and their employment position. The positive tenure association may therefore reflect both accumulated work exposure and a lower sickness-reporting threshold among more established Runners. The survival analysis can help clarify this mechanism by showing whether the tenure association is mainly related to slower return-to-work, or instead to short-term reporting behaviour.

Commuting distance differs between France and Germany, making it difficult to identify one clear mechanism. The distance variables may capture commuting burden, but they may also proxy unobserved local characteristics, such as the type of area employees live in, public transport access, urban density, local labour-market composition, or site-specific recruitment patterns. Therefore, the distance coefficients should be interpreted as contextual employee-profile associations rather than direct evidence that commuting distance itself increases or decreases absence.

The scheduling block suggests that recent work-pattern composition is related to Runner absence, although not all coefficients are equally interpretable. The number of shifts mainly controls for recent work exposure and has high VIF values, so it should not be read as a clean independent effect. The weekday pattern suggests that Runner absence is higher around regular working-week exposure, especially Monday and the Tuesday-to-Thursday reference pattern, while Friday and weekend work are associated with lower absence, possibly because these schedules reflect different availability or selection patterns. Shift-time results also suggest that afternoon shifts are associated with higher absence than morning shifts. However, the evening/night coefficient should be interpreted cautiously because of high VIF values. Overall, the scheduling results suggest that Runner absence is related not only to how much employees work, but also to when that work is scheduled.

For operational and team-context variables, driving score is only meaningfully interpretable in Germany, where there is sufficient variation. Stronger Runner performance in the German model suggests that performance is associated with lower absence (β = -.014). In France and the Netherlands, there is too little variation in this variable to draw a meaningful conclusion. Captain absence rate shows a clear positive association with Runner absence in all three countries, making it one of the strongest operational-context findings in the Runner OLS. This may still reflect the importance of shared team conditions and broader site-level operational circumstances, rather than a direct causal effect of captain absence itself.

The exogenous controls are also relevant, Influenza is positively and significantly associated with Runner absencein France (β = .020) and Germany (.022), which is consistent with the expectation that seasonal health shocks increase sickness absence. Economic growth also shows a relationship with lower sickness absence in the Netherlands (β = -.011) and France (-0.010), aligning with expectations. Major operational disruptions show relevant significant relationships in France (β = .012) but less in Germany (-.006). The positive French coefficient is more consistent with the expected interpretation that operational disruptions increase sickness absence.

4.2.2 Robustness OLS

Shopper

Table 4: Shopper robustness absence-rate OLS models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Walking distance; Monday–Thursday shifts; Afternoon shifts; Ambient shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Female	0.026	0.031	-0.010
Age 26–40	-0.034	-0.008	-0.108***
Age 40+	-0.033	-0.056**	-0.116***
Tenure 94–187 days	0.005	0.177***	-0.102***
Tenure 188–365 days	-0.062	0.150***	-0.089***
Tenure 366–730 days	-0.112	0.091***	-0.098***
Tenure 731–1095 days	-0.115	0.039†	-0.059***
Tenure 1096–1460 days	-0.046	0.006	-0.034***
Tenure 1461+ days	0.060		-0.031***
Distance			
Biking distance	0.070†	-0.009	0.009
Driving distance	0.051	-0.004	-0.018
Scheduling: total volume			
Total shifts in observation period	0.150**	0.321***	0.242***
Scheduling: weekday composition			
Friday shifts	0.053	-0.030	0.037*
Weekend shifts	-0.015	0.036†	0.021†
Scheduling: shift time			
Morning shifts	0.036	-0.168***	0.009
Evening/night shifts	0.037		-0.030***
Scheduling: shift type			
Chilled shifts	-0.300***	-0.426***	-0.359***
Frozen shifts	-0.081***	-0.094***	-0.013*
Operational and performance context			
People per shift	0.005	0.007	0.126***
Picking/replenishment speed	0.026	0.061*	-0.078***
Late shifts	-0.032	-0.165***	-0.174***
Leadership/team context			
Captain absence rate	-0.010	0.108***	0.041***
Exogenous controls			
Influenza level	0.089*	-0.058**	-0.021†

Variable	NL	FR	DE
Economic growth	0.004	-0.070***	0.186***
Major operational disruptions	0.028	0.048*	0.008

Notes: Coefficients are standardized OLS estimates from the person-level robustness models. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model because of too little variance.

The Shopper robustness OLS provides partial validation of the main person-week OLS. The clearest overlap is found for the shift type variables: Chilled and Frozen shifts remain negatively associated with absence in all three countries, which supports the main OLS finding that these shift types are linked to lower Shopper absence rates. The French tenure pattern is also broadly similar, with early and medium-tenure groups remaining positively associated with absence. In addition, late shifts remain negatively associated with absence in France and Germany, and Captain absence remains positive in France and Germany.

However, several Shopper results are less stable after aggregation. Female becomes insignificant in all countries, while the positive age effects from the main OLS in the Netherlands and France disappear or change direction. Some scheduling variables also become less consistent: total shifts become positive in all countries, while Friday and weekend shifts no longer clearly validate the main OLS pattern. Performance is also mixed, since picking/replenishment speed remains positive in France but becomes negative in Germany. This means that the robustness model confirms some broad patterns, especially shift type and French tenure, but does not fully validate all worker-profile and scheduling associations.

The main limitation is that several robustness coefficients have high VIFs and are therefore not well separately interpretable. This applies especially to total shifts, Friday shifts, people per shift, Captain absence rate, and in some countries morning shifts, driving distance, Dutch tenure categories, and economic growth. These VIFs are high because the robustness model is aggregated to one observation per employee: weekly variation is collapsed, so variables that normally vary across weeks start to measure the same long-run employee or site pattern. For example, total shifts, Friday shifts, weekend shifts, and morning shifts are mechanically related parts of an employee's overall schedule, while people per shift and Captain absence may both proxy site context. Therefore, the robustness OLS should be used mainly as a broad validation check, not for precise interpretation of high-VIF scheduling and team-context coefficients.

Runner

Table 5: Runner robustness absence-rate OLS models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Walking distance; Monday–Thursday shifts; Afternoon shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Female	0.062†	0.096***	0.041***
Age 26–40	0.053†	0.021	0.033***
Age 40+	0.126**	-0.023	-0.001
Tenure 94–187 days	0.012	0.172***	-0.009
Tenure 188–365 days	0.008	0.094**	-0.056***

Tenure 366–730 days	0.065†	0.033	-0.036***
Tenure 731–1095 days	0.049	0.034	-0.019***
Tenure 1096–1460 days	0.116***	0.006	0.016
Tenure 1461+ days	0.099*		-0.009†
Distance			
Biking distance	0.025	-0.043	-0.001
Driving distance	0.032	0.008	0.019*
Scheduling: total volume			
Total shifts in observation period	0.078	0.172*	0.144***
Scheduling: weekday composition			
Friday shifts	-0.086*	0.007	-0.085***
Weekend shifts	-0.075*	-0.101***	-0.084***
Scheduling: shift time			
Morning shifts	0.027	-0.012	-0.015
Evening/night shifts	-0.051	-0.069	-0.067***
Operational and performance context			
Driving score			-0.009
Late shifts	-0.023	-0.097***	-0.040***
Leadership/team context			
Captain absence rate	-0.011	-0.007	0.011
Exogenous controls			
Influenza level	0.017	-0.006	-0.027**
Economic growth	-0.038†	-0.067***	0.143***
Major operational disruptions	-0.020	0.024	-0.007

Notes: Coefficients are standardized OLS estimates from the person-level robustness models. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model because of too little variance.

The Runner robustness OLS also provides partial validation of the main OLS. Female remains positively associated with absence in all three countries, which supports the main Runner OLS pattern. Weekend shifts are also consistently negative in all three countries, and Friday shifts remain negative in the Netherlands and Germany. Some tenure patterns are also similar: Dutch long-tenure groups remain positively associated with absence, while French early-tenure groups remain positively associated with absence.

At the same time, several Runner results are not robust to aggregation. Total shifts become positive in France and Germany, whereas the main OLS showed negative associations there. Morning shifts lose their earlier negative association, and evening/night shifts remain clearly negative only in Germany. Captain absence is also no longer positively associated with Runner absence, even though this was one of the more consistent findings in the main OLS. Late shifts change as well: they are negative in France and Germany in the robustness model, while the main OLS showed a more mixed pattern. This suggests that the robustness model validates broad profile and weekend-scheduling patterns, but not the more detailed operational-context findings.

The Runner robustness VIFs are especially high for total shifts, evening/night shifts, people per shift, Dutch tenure groups, Dutch morning shifts, and German driving score. These variables should therefore be interpreted cautiously. The reason is again the person-level aggregation:

once all weeks are collapsed into one employee-level observation, schedule-volume and schedule-composition variables become strongly correlated. Employees with many total shifts also tend to have more shifts in specific time categories, and people per shift may overlap with site size, route structure, or operational scale. Therefore, the Runner robustness model is useful for checking whether general findings remain visible, but exact coefficient-level interpretation is weak for the high-VIF variables.

4.2.3 Results synthesis

The OLS results show that sickness absence is not explained by one general mechanism across logistics' frontline workforce. Instead, absence is structured by a combination of employee profile, role-specific work patterns, country context, and local operational conditions. Because the OLS models estimate the weekly absence rate, the coefficients capture the overall absence burden rather than one specific absence mechanism. A higher absence rate may therefore reflect more frequent spells, longer spells, or both. The OLS results should consequently be interpreted as indicators of where absence concentrates, while the survival analysis is needed to assess whether these patterns are mainly related to absence duration and return-to-work.

One of the most important employee-profile findings is the country-specific role of contract type. Permanent contracts are positively associated with absence in the Netherlands, but negatively associated with absence in Germany, for both Shoppers and Runners. Because age and tenure are already controlled for, this opposite sign cannot be explained only by permanent employees being older or more tenured. Instead, permanent contract status appears to capture a different mechanism across countries. This may reflect differences in employment security, worker selection or contract-allocation practices. This finding is practically relevant for logistics, especially if the organisation moves towards a larger share of permanent contracts. The German pattern suggests that permanent contracts can be associated with lower absence compared with fixed-term contracts, while the Dutch pattern points in the opposite direction. Understanding how German selection practices differ from the Dutch context may therefore be valuable for future HR policy.

Gender is the most consistent employee-profile association across the OLS models. Female employees are associated with higher sickness absence among both Shoppers and Runners in all three countries. This does not explain why the association exists, but it does indicate that gender remains relevant after controlling for age, tenure, contract type, commuting distance, scheduling, operational context, and exogenous factors. It should therefore be treated as one of the clearest workforce-composition findings in the OLS results.

Age and tenure show more role-specific patterns. In the Shopper models, the age association differs clearly by country. In the Netherlands and France, higher absence is concentrated among older Shoppers, while in Germany the negative coefficients for older groups suggest that absence is relatively higher among the youngest reference group. This points to potentially different absence margins. In the Netherlands and France, older Shopper absence may be more related to longer-duration absence, whereas in Germany the higher absence among younger Shoppers may be more related to short-term reporting behaviour or early workforce attachment, the subsequent survival analysis will enable deeper interpretation of this mechanism.

For Runners, tenure shows a more consistent positive relationship with sickness absence. Because age and other relevant profile variables are controlled for, this is not simply an ageing effect. Longer-tenured Runners may feel less constrained to report sick because they are more familiar with the organisation, absence procedures, and their employment position. The survival analysis can help clarify whether higher-tenure Runners also have longer sickness spells and slower return-to-work. This may then partly explain why Runners show relatively more medium- and long-duration absence than Shoppers in the exploratory analysis.

The scheduling results show that absence is also related to when and where employees work, although some coefficients require caution because of multicollinearity. For Shoppers, the clearest operational scheduling result is that Chilled and Frozen shift exposure is consistently associated with lower absence than Ambient work. The Dutch Shopper model also uniquely shows higher absence for Friday shifts. This may point to leisure-related timing effects, especially in a context without a formal doctor's note requirement and with only conditional waiting days. Weekend effects are weaker after controlling for other variables than in the exploratory plots, but still suggest that weekend work may reflect different availability or selection patterns. For Runners, absence is more strongly linked to regular working-day exposure, while Friday and weekend work are associated with lower absence. These differences between Shoppers and Runners are important because weekday effects should theoretically be limited if sickness absence were driven only by illness. Their presence therefore supports the behavioural interpretation of sickness absence.

Team context is another recurring operational finding. Captain absence is positively associated with sickness absence in several models, especially in Germany and France, and is particularly consistent for Runners. The stronger relationship in Germany and France may also indicate that Captain absence is more informative in these contexts, potentially because Captain roles are more selectively assigned or because local team structures differ. The coefficient should not be interpreted as Captain absence directly causing employee absence, but it does point to the importance of local team context.

Other operational variables confirm that operational context matters, but their interpretation is less consistent across countries. People per shift shows the clearest expected pattern in Germany, where it is positively associated with absence and validated in the robustness analysis. This suggests that larger operational environments may be linked to higher sickness absence, potentially through less peer pressure. In other countries, however, other operational variables show mixed signs or weaker robustness, making strong cross-country conclusions difficult. Driving score is mainly interpretable in Germany, where sufficient variation allows the model to identify a small negative association with Runner absence. A similar relationship may exist in the Netherlands or France, but limited variation in the current setup makes it difficult to detect reliably. Overall, these findings underline the relevance of operational context, while also showing that operational coefficients require careful interpretation and validation through robustness checks.

The exogenous variables add further context, especially for Runner absence. Major operational disruptions are more strongly associated with Runner absence than Shopper absence, specifically is France. Disruptions such as road problems, severe weather, protests, or delivery-route disturbances may make Runner work more difficult or less attractive on affected days. In that sense, disruptions may lower the threshold for reporting sick. This interpretation fits the behavioural view of sickness absence: external conditions do not need to cause illness directly to influence absence reporting. Influenza is also relevant in several Runner models, especially in France and Germany, which is more consistent with a genuine seasonal health-shock mechanism. Overall, the exogenous controls are not the central explanatory block of the OLS results, but they help distinguish health-related external shocks from disruption-related conditions that may influence the absence-reporting threshold.

Overall, the OLS results point to several findings that should be carried forward into the survival analysis and final synthesis. These findings remain associative, but they show that sickness absence is shaped by more than national policy alone. Employee composition, contract practices, scheduling, team context, and local operations all help explain where absence concentrates. At the same time, patterns such as weekday differences, tenure variation and disruption sensitivity suggest that sickness absence also contains a behavioural component: workers' reporting decisions appear to be shaped not only by illness.

4.3 Survival Analysis

4.3.1 Kaplain Meier Survival Curves

The Kaplan–Meier curves provide an initial descriptive comparison of sickness absence spell duration across countries and employee types. The vertical axis represents the estimated probability that a sickness spell is still ongoing after a given number of days. A steeper decline therefore indicates that employees tend to return sooner, while a flatter curve indicates that absence spells are more likely to continue for longer.

The Kaplan–Meier curves, can be found in Appendix I, and motivate the use of survival analysis in the next step. Simple averages of spell duration may be strongly influenced by a small number of very long spells, whereas the survival framework analyses the duration process more directly over time. The subsequent Cox proportional hazards models examine whether employee characteristics, job-context variables, and country-specific factors are associated with the rate at which sickness absence spells end. In this interpretation, a higher hazard ratio indicates a faster return from sickness absence and therefore shorter spells, while a lower hazard ratio indicates a lower return rate and therefore longer sickness absence spells.

4.3.2 Multivariate Cox proportional hazards models

The tables report standardized Cox log-hazard coefficients by country and include the concordance index and observations per model. Tables including the VIF values of each coefficient are shown in Appendix H.

The models examine which factors are associated with sickness absence duration. Because the Cox model estimates the return-to-work hazard, positive coefficients indicate a higher probability of returning to work and therefore shorter absence spells. Negative coefficients indicate a lower return-to-work hazard and therefore longer absence spells.

Shoppers

Table 6: Shopper survival models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Biking distance; Monday–Thursday shifts; Afternoon shifts; Ambient shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Permanent contract	-0.029		0.001
Female	-0.019	-0.030	-0.021**
Age 26–40	-0.040*	-0.066**	-0.037***
Age 40+	-0.116***	-0.086***	-0.090***
Tenure 0–93 days	-0.009	0.038	0.029***
Tenure 94–187 days	0.002	0.037	0.020**
Tenure 188–365 days	-0.003	0.064**	-0.002
Tenure 731–1095 days	0.006	-0.028†	-0.017**
Tenure 1096–1460 days	-0.008	0.025***	-0.004
Tenure 1461+ days	-0.004		-0.012†
Distance			
Walking distance	0.010	0.011	-0.018**
Driving distance	0.005	-0.023	0.006
Scheduling: total volume			
Total shifts in previous 4 weeks	-0.096***	-0.088***	-0.120***
Scheduling: weekday composition			
Friday shifts	-0.047*	0.025	-0.047***
Weekend shifts	0.037*	0.008	0.003
Scheduling: shift time			
Morning shifts	-0.003	0.008	-0.006
Evening/night shifts	0.035*		0.005
Scheduling: shift type			
Chilled shifts	0.069***	0.099***	0.075***
Frozen shifts	-0.011	0.028	0.017**
Operational and performance context			
People per shift	-0.013	0.015	-0.028***
Picking/replenishment speed	0.002	0.003	0.007
Late shifts	-0.012	0.061***	0.064***
Leadership/team context			
Captain absence rate	0.006		-0.055***
Exogenous controls			
Influenza level	-0.034*	-0.017	0.012*
Economic growth	-0.014	0.022	-0.032***
Major operational disruptions	0.008	-0.025	0.028***
Model fit			
Concordance index	0.602	0.588	0.604
Observations	5459	4053	38536

Notes: Coefficients are standardized Cox proportional hazards estimates. Positive coefficients indicate a higher return-to-work hazard and therefore shorter sickness absence spells. Negative coefficients indicate a lower return-to-work hazard and therefore longer sickness absence spells. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model.

The Shopper survival models examine return-to-work dynamics after a sickness spell has started. Unlike the absence-rate OLS, the survival models do not explain whether employees report sick, but how long they remain absent once a spell occurs. The concordance indices are modest, ranging from .588 in France to .604 in Germany, which indicates that the models capture meaningful patterns in return-to-work behaviour, but that a substantial share of spell-duration variation remains unexplained. This is expected, because sickness duration is strongly affected by unobserved health severity, diagnosis, recovery conditions, and private circumstances that are not available in the administrative data. Generally, Germany has more significant survival results than the other countries, which is partly expected because the German sample is larger and contains more variation.

Employee-profile effects are less uniform than in the absence-rate OLS. Contract type is not significantly associated with Shopper return-to-work once other variables are controlled for. This suggests that the longer durations observed for permanent contracts in the exploratory analysis are likely explained by other characteristics, especially age and tenure, rather than by contract type itself. Age remains important: older Shoppers generally have slower return-to-work, which is consistent with the exploratory finding that older employees are more represented in longer-duration absence. Shoppers aged 40 or above show lower return-to-work hazards in the Netherlands (β = -.116)), France (-.086), and Germany (-.090). Tenure is country-specific. In the Shopper survival models, tenure shows opposite duration-related patterns in France and Germany. The results show slightly opposite tenure patterns in France and Germany. Higher-tenure Shoppers generally return to work faster in France, but slower in Germany. Although these results are not among the strongest survival findings, they help clarify the OLS patterns. In Germany, the high absence rate among the youngest Shopper reference group is more likely to reflect short-term absence. In France, the faster return to work among higher-tenure Shoppers suggests that tenure does not primarily capture eligibility for tenure-based policy benefits. Instead, the higher absence rate among these groups appears to be related mainly to more frequent short-term absence.

Commuting distance has limited but notable country-specific relevance. In Germany, Shoppers living close to the fulfilment centre are associated with longer sickness spells (β = -.018)). This should not be interpreted as a direct effect of living nearby. It may instead capture unobserved characteristics of the residential areas around fulfilment centres, such as urban density, socioeconomic conditions, or worker selection into nearby housing. As with the OLS absence-rate models, commuting distance is therefore better interpreted as a contextual proxy than as a pure commuting-burden mechanism.

The scheduling results are especially important because, unlike in the OLS robustness models, the survival model does not show major VIF problems. This means that total shifts can be interpreted more directly. More shifts in the previous period are associated with slower return-to-work among Shoppers in the Netherlands (β = -.096)), France (-.088)), and Germany (-.120)). A plausible interpretation is that higher recent scheduling volume may proxy higher workload, fatigue, or stronger work exposure before the sickness spell. This could indicate that employees who worked more intensively before becoming sick also need longer recovery time. Friday-shift exposure is also associated with longer spells, and Dutch weekend exposure appears to point in the same direction. These patterns may say something about the type of employees scheduled on these days, rather than the days themselves. Weekend and Friday workers may differ in availability or role within the operational schedule.

Shift type is one of the clearest Shopper survival findings. Chilled shifts are associated with shorter sickness spells in the Netherlands (β = .069)), France (.099)), and Germany (.075)), and Frozen shifts show a similar pattern in some models. This is consistent with the absence-rate OLS, where Chilled and Frozen shifts were associated with lower absence rates. One possible explanation is that the sickness spells among these workers are more often temperature-zone-related short illnesses, such as minor colds, rather than longer recovery-related cases. However, the model cannot distinguish diagnosis type, so this interpretation remains tentative.

Several operational-context variables are especially relevant in Germany. More people per shift (β = -.028) and higher Captain absence (β = -.055) are associated with longer Shopper absence spells. This may indicate that larger team contexts or weaker leadership continuity reduce the pressure or support to return quickly. Late-shift exposure, by contrast, is associated with shorter spells. This result may point to a short-term behavioural mechanism: employees with more late-shift exposure may be more likely to have shorter spells, possibly linked to motivation, or attendance reliability. However, because the OLS model does not show a positive association between late-shift exposure and the overall absence burden, this interpretation should remain cautious.

The exogenous variables are most relevant in Germany. Influenza is associated with shorter-term absence dynamics(β = .012)), which fits the type of illness: influenza-related absence is often acute and relatively short compared with long-term recovery cases. German major operational disruptions suggest sickness absence related are short (β = .028)). This aligns with the OLS interpretation that disruptions may be linked to short-term, threshold-sensitive absence. Disruptions may make Runner work feel more burdensome or provide incentive not to work, lowering the threshold for reporting sick. However, OLS model does not show a positive association with the absence burden, so this short-term effect might not influence operations that significantly. Economic growth is associated with longer absence(β = -.032)), which may reflect the higher labour demand, through changing employee bargaining position.

Runners

Table 7: Runner survival models

Reference categories: Male; Age below 26 years; Tenure 0–93 days; Walking distance; Monday–Thursday shifts; Afternoon shifts; No major operational disruptions.

Variable	NL	FR	DE
Employee profile			
Permanent contract	-0.015		-0.006
Female	-0.031	-0.019	-0.013*
Age 26–40	0.008	-0.079**	-0.084***
Age 40+	-0.111***	-0.052*	-0.087***
Tenure 0–93 days	0.012	0.078**	0.059***
Tenure 94–187 days	0.009	-0.041	0.021**
Tenure 188–365 days	-0.020	-0.050†	-0.003
Tenure 731–1095 days	0.002	0.020	-0.004

Tenure 1096–1460 days	-0.028	0.030***	-0.009**
Tenure 1461+ days	-0.014	-0.006	-0.007†
Distance			
Walking distance	0.006	-0.016	-0.005
Driving distance	-0.012	0.023	0.004
Scheduling: total volume			
Total shifts in previous 4 weeks	-0.048†	-0.016	0.003
Scheduling: weekday composition			
Friday shifts	0.056†	0.031	0.015*
Weekend shifts	0.079**	0.109***	0.025***
Scheduling: shift time			
Morning shifts	-0.031	0.031	-0.006
Evening/night shifts	0.037	-0.019	0.025***
Operational and performance context			
Driving score	-0.040	-0.046†	0.003
Late shifts	-0.022	0.056*	0.011†
Leadership/team context			
Captain absence rate	-0.023		0.006
Exogenous controls			
Influenza level	-0.001	0.013	-0.001
Economic growth	0.007	0.003	0.011†
Major operational disruptions	0.012	-0.008	0.030***
Model fit			
Concordance index	0.590	0.593	0.565
Observations	1853	1602	35760

Notes: Coefficients are standardized Cox proportional hazards estimates. Positive coefficients indicate a higher return-to-work hazard and therefore shorter sickness absence spells. Negative coefficients indicate a lower return-to-work hazard and therefore longer sickness absence spells. Significance levels: $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Blank cells indicate that the variable was not included in that country-specific model.

The Runner survival models explain return-to-work dynamics after a sickness spell has started. Overall, the results show that absence duration is more clearly related to employee profile and selected scheduling characteristics than to contract type, commuting distance, or performance. The concordance indices indicate modest predictive performance across the three countries, with values of .590 in the Netherlands, .593 in France, and .565 in Germany, meaning that the models identify some meaningful return-to-work patterns but leave a substantial share of duration variation unexplained. This is expected, because sickness spell duration is likely influenced by unobserved factors such as illness severity, diagnosis, recovery conditions, private circumstances, and case-management processes. The German model contains more significant coefficients, which is partly expected given the larger German dataset: with more observations, smaller associations are more likely to become statistically significant. Therefore, statistical significance should again be interpreted together with effect direction, plausibility, and model diagnostics.

The clearest employee-profile result is age. Older Runners are generally associated with slower return to work, especially the 40+ group, in the Netherlands (β = -.111), France (-.052), and Germany (-.087). This is consistent with the exploratory analysis and with the broader sickness-absence literature, where older workers often have fewer but longer absence spells. Tenure shows a related but more country-specific pattern. Longer-tenured Runners are generally associated with slower return to work, suggesting that more established workers may have longer-duration absence once they become sick. These groups might therefore susceptible to long-term wage replacement rates rather than short-term policy incentives.

Similair to Shoppers, tenure has inconsistent country-specific effects. The longest-tenured French Runners return to work faster (β = .030). This may reflect selection among the relatively small group of long-tenured French Runners, stronger attachment, or different absence behaviour among employees who remain with the organisation longer. In Germany the same mechanism is true for newer employees (β = .059). Contract type does not show a clear significant relationship with duration, suggesting that contract differences observed descriptively are likely explained by correlated factors such as age, tenure, or workforce composition.

Commuting distance is not a significant determinant of Runner absence duration. This differs from some of the absence-rate results and may be explained by the role context: Runners generally live closer to their hub than Shoppers live to fulfilment centres, so there may be too little meaningful distance variation for commuting distance to explain return-to-work speed. Therefore, distance appears less relevant for Runner spell duration than for some other parts of the analysis.

Total shifts has high VIFs in the Runner survival model and should therefore not be interpreted as an independent effect of scheduling volume. However, Friday, weekend and German Evening/night shifts are associated with faster return to work and therefore shorter absence spells(β = .015, .025, .025)). Similair to the shopper model, this result may relate to the Runner population working Fridays and weekends. However, as this concerns short-term absence it may also be related to the shift itself, more suggestive of being related to leisure activities in the weekend.

Operational variables are more limited. However, the Runner survival models show a similar pattern to the Shopper survival models. Lateness is associated with short-term absence, which may indicate sickness absence related to motivation. Major operational disruptions are also associated with shorter Runner spells in Germany (β = .030)). This supports the interpretation that disruptions may lower the threshold for reporting sick when work feels more burdensome, while the resulting absences remain relatively short. These findings should therefore be interpreted as suggestive duration patterns, not as general operational effects.

4.3.3 Results synthesis

The survival results show that return-to-work is partly explained by employee profile, scheduling exposure, and operational context, but less strongly than the OLS absence-rate models. This is expected because the survival analysis only includes observed sickness spells, while the OLS models use the full person-week dataset. The smaller survival sample reduces statistical power, especially in the Netherlands and France. Germany shows more significant results, which is plausibly related to its larger spell sample and greater operational variation. Some relationships found in Germany may therefore also exist in the other countries, but remain undetected due to data limitations.

Compared with the OLS models, the survival results are more similar across Shoppers and Runners. Whereas the OLS results showed clearer role-specific absence-rate patterns, the survival models point to more general return-to-work mechanisms. Once employees are sick, age, recent work exposure, and selected operational conditions appear more relevant than the detailed role-specific differences observed in the absence-rate models.

Age is the clearest duration-related employee-profile factor. Older employees generally return to work more slowly in both roles. This is a plausible and important finding: older workers may need longer recovery once sickness absence occurs. Unlike some short-term absence patterns, this result is more consistent with legitimate recovery-related absence than with discretionary reporting behaviour.

Contract type is less informative for absence duration than for the overall absence rate. After controlling for age, tenure, and other relevant variables, permanent contract status does not show a clear relationship with return-to-work. This suggests that the contract-type differences found in the OLS models are more likely related to absence occurrence, workforce composition, or selection into contract types than to the length of sickness spells once absence has started.

Tenure is country-specific in both roles. It is not a clear predictor of return-to-work in the Netherlands, while longer-tenured employees generally return faster in France and newer employees return faster in Germany. The French result is especially relevant because higher-tenure employees had higher absence rates in the OLS models. The survival results suggest that this French tenure pattern is probably not driven by longer sickness spells, but more likely by short-term absence or higher absence occurrence among longer-tenured employees.

Commuting distance does not produce a clear duration-related interpretation. Any distance effects are country-specific and inconsistent, which suggests that commuting distance is not a central predictor of return-to-work. As in the OLS models, distance is better interpreted as a contextual proxy than as a direct commuting-burden mechanism.

Recent scheduling volume is more informative in the Shopper survival models. More shifts in the previous period are associated with slower return-to-work among Shoppers in all countries. This suggests that recent work intensity may be linked to longer recovery, potentially through workload, fatigue, or accumulated operational exposure before the sickness spell. This points to a possible work-related avoidable absence margin: not discretionary absence, but sickness duration that may be partly connected to intensive operational exposure.

Several scheduling results point to short-term absence rather than long-duration sickness. For Runners, Friday and weekend exposure are associated with faster return-to-work, suggesting that these absences are relatively short and may reflect scheduling-population differences or threshold-sensitive absence around specific shifts. A similar pattern is partly visible for Dutch Shoppers. For Shoppers, Chilled and Frozen shifts are also associated with shorter spells, which aligns with the OLS finding that these shift types have lower absence rates. This makes shift type one of the clearest Shopper findings, although it may reflect selection into work areas rather than a direct effect of temperature zone.

Operational-context variables matter, but their interpretation remains cautious. People per shift is associated with longer absence, suggesting that larger or more complex team settings may reduce focused return-to-work pressure or reflect heavier operational environments. Captain absence and lateness are more often associated with shorter spells. This may point to short-term behavioural absence among specific groups, possibly linked to weaker attendance motivation, local team dynamics, or reduced day-to-day pressure, rather than to long recovery processes.

The exogenous variables help distinguish health shocks from behavioural or operational triggers. Influenza shows the expected short-term sickness pattern: it is related to absence, but not necessarily to long-duration spells. Economic growth is associated with longer absence, which may reflect stronger labour demand, lower job insecurity, or greater employee bargaining position. Major operational disruptions are associated with shorter spells, specifically in Germany ,supporting the interpretation that disruptions may lower the threshold for reporting sick when a shift feels unusually burdensome or when better alternatives exist. These absences appear more consistent with skipped individual shifts than with longer sickness cases. However, a higher absence rate was found only in France. The significantly shorter spells observed in Germany may therefore have limited implications for the overall absence burden, although they may still disrupt operations by creating unexpected gaps in individual shifts.

Overall, the survival analysis sharpens the OLS interpretation by separating absence burden from absence duration. Older-worker effects and recent scheduling intensity point toward recovery-related or work-exposure mechanisms. Contract type appears less relevant for duration than for absence occurrence. French tenure effects and weekend/disruption patterns appear more consistent with short-term absence. These findings show that sickness absence contains multiple margins: legitimate recovery, work-related strain, workforce selection, and threshold-sensitive reporting behaviour.

4.4 Operational and Policy strategy foundation

The previous sections show that sickness absence cannot be explained by policy, employee characteristics, or operational context in isolation. The exploratory policy analysis showed where national sickness absence frameworks appear aligned with observed absence frequency and duration patterns. The OLS models then showed where the overall absence burden concentrates, while the survival models clarified which patterns are more related to return-to-work and spell duration. This final results section brings these findings together to identify which patterns are most relevant for operational action and which patterns are more useful for broader policy and context reflection. A brief recommendation for operational and policy actions are discussed in Chapter 5.2.

4.4.1 Recurring operational patterns

Recurring operational patterns are findings that appear across countries, roles, or model types and therefore point less to one national policy framework and more to general workforce, scheduling, team, or other operational context.

For Shoppers, a clear operational result is the contrast between Ambient and Chilled/Frozen work. Chilled and Frozen shift exposure is associated with lower absence rates in the OLS models, while the survival analysis suggests that cold-zone exposure is more strongly associated with short-term rather than long-term absence. However, this should not be interpreted as evidence that cold-zone work directly reduces sickness absence. The lower overall absence rate may reflect selection into these shifts, stronger work attachment, more stable workers, or different routines. At the same time, the stronger short-term association, apparent from survival analysis, means that a cold-zone mechanism cannot be ruled out completely: cold exposure may still contribute to short, temporary complaints, such as minor illness or cold-related discomfort, even if these spells do not persist into longer-duration absence. Logistics can therefore use this finding to compare Ambient and cold-zone work in terms of clothing, rotation, supervision and employee selection. Better preparation for cold work, suitable protective clothing, and clearer expectations may help reduce avoidable short-term work-related absence among employees who are less adapted to cold-zone tasks.

A second Shopper-related operational finding concerns recent scheduling intensity. The survival results indicate that Shoppers with more shifts in the preceding period have longer sickness spells. Because this is a duration result, it points less to purely discretionary short-term reporting and more to recovery-related or workload-related mechanisms. One plausible interpretation is that heavier recent scheduling contributes to fatigue or physical strain, making recovery slower once sickness absence occurs. Another possibility is a presenteeism pathway: employees with high recent work exposure may continue working while unwell and only report sick when symptoms become more severe, leading to longer recovery. The practical implication is not simply to reduce shifts, but to monitor accumulated workload, repeated intensive rosters, recovery time between shifts, and the distribution of physically demanding work.

Another recurring workforce-composition finding is that female employees are associated with higher sickness absence across both roles and all countries. This should not be interpreted as an operational lever in itself, but it indicates that absence patterns differ systematically across employee groups even after controlling for factors like contract type, age and tenure. The results follows results found in previous research, and has been shown before that females have a larger sickness absence strongly linked to legitimate recovery. For logistics, this suggests that absence monitoring should remain sensitive to workforce composition and possible differences in work-life constraints and health exposure without drawing conclusions at individual level. Adjacently, age is the clearest recurring duration-related profile pattern. Older employees generally return to work more slowly once sickness absence has started. This also points more toward legitimate recovery and longer recovery needs than toward discretionary absence. For logistics, this suggests that return-to-work support, workload adaptation, and reintegration guidance may be especially relevant for older workers, particularly where absence spells become longer.

For Runners, tenure appears more relevant than for Shoppers in explaining absence burden. The OLS results suggest higher absence among longer-tenured Runners, while the survival models indicate that tenure may also relate to faster return-to-work in some countries. This may reflect accumulated exposure to delivery work, greater familiarity with absence procedures, or lower perceived constraints around reporting sick or remaining absent. Because the survival evidence is not uniform across countries, this should be interpreted as a role-specific signal rather than a definitive mechanism.

Timing-related and behavioural indicators provide additional but more cautious signals. For Runners, Friday and weekend exposure are generally associated with lower absence rates and shorter spells, but this should not be interpreted as evidence that these days directly reduce sickness absence. A more plausible explanation is that Runners working Fridays and weekends form a more selected or attached subgroup, with stronger availability, being mostly sched. For Shoppers, weekday effects are less consistent. In the Netherlands, Friday exposure is associated with higher absence, which may point more towards timing-sensitive or discretionary absence behaviour, while the higher weekend absence observed in the exploratory plots does not remain clearly significant once other variables are controlled for. Overall, the scheduling results suggest that timing variables are useful indicators of workforce segmentation, work routines, job attachment, and operational context, but they should not be treated as clean causal effects of specific days or shift times. Weekday, weekend, shift-time, and total-shift variables partly overlap, and some scheduling variables show multicollinearity, especially in the aggregated robustness models. Therefore, the robust conclusion is not that each individual weekday or shift-time coefficient has a clear independent meaning, but that scheduling patterns capture meaningful differences in employee composition and work routines. Lateness and performance-related variables should be interpreted similarly: they may signal weaker work attachment, less stable routines, or differences in reliability, but they should not be used to infer motivation or legitimacy at the individual level.

A second group of findings concerns local team and operational context. Captain absence is associated with higher absence in several models, especially for Runners in the main OLS models and for Shoppers in France and Germany. Although this relationship is not always fully validated in the robustness models, it suggests that absence may cluster within local teams or sites. Captain absence is therefore best interpreted as an indicator of broader local conditions, such as team or site norms, morale, and shared workload. This is actionable for logistics because such clustering may point to an operationally avoidable absence margin. Where these associations are strongest, targeted interventions may help address the underlying local conditions associated with higher absence. The main operational implication is therefore not to focus narrowly on Captains, sructurally high Captain absence may help identify teams or sites experiencing broader operational difficulties and could be used to target local support and operational improvements.

The importance of local context is also visible in the exploratory analysis, where absence varies strongly between fulfilment centres and hubs. If national policy were the dominant explanation, absence patterns would be expected to be more homogeneous within countries. Instead, the location-level variation suggests that site-level management, staffing pressure, team composition, local norms, and operational conditions explain part of the remaining variation. Some German survival findings reinforce this interpretation: German Shoppers with more people per shift and higher Captain absence show longer sickness spells, which may point to larger operational scale, weaker leadership continuity, lower return pressure, or shared site-level working conditions. These findings indicate that local operational diagnosis is necessary before designing interventions.

Exogenous findings form a third, but less actionable, consistent layer across countries, which are generally aligned with a genuine health-shock and labour demand interpretation. Influenza results, logically align with legitimate recovery. Whereas, positive absence findings related economic growth might be explained through a lower absence-threshold for reporting sick.

4.4.2 Country-specific absence patterns

The recurring operational findings show which mechanisms may be relevant across lgistics' operations. The country-specific analysis adds a second step: it examines where the same type of variable has a different meaning across national contexts. This is especially important for employee-profile variables such as age, tenure, and contract type, because these do not reflect the same workforce segment in every country. The country sections below therefore interpret the main result, whether it appears mainly operational, policy-related, or both, and what type of absence margin it most likely suggests.

In **the Netherlands**, two absence margins stand out: very short-term absence and long-term absence. These two patterns likely reflect different mechanisms and should therefore not be interpreted as one single Dutch absence problem. For long-term absence, the main result is that the Dutch absence burden is more strongly connected to older and more established employees. In the OLS models, age has a stronger positive association with absence rate in the Netherlands than in Germany and France, even after controlling for related factors such as tenure and contract type. The survival analysis shows that longer sickness spells are mainly related to age, but this age-duration relationship is not uniquely Dutch; it is also visible in Germany. Therefore, the Dutch long-term absence pattern is not simply explained by age having a stronger duration effect in the Netherlands. A more plausible interpretation is that the Dutch workforce contains relatively more older and established employees, and that this composition makes age-related recovery dynamics more visible in the Dutch absence burden. At the same time, policy remains a plausible part of the explanation. The Netherlands has the most extensive long-term institutional setting, with long employer-payment obligations and relatively high effective wage replacement. This does not mean that policy causes long-term absence directly, but it may make age- and recovery-related absence more persistent or more costly once it occurs. The suggested absence type is therefore mainly legitimate recovery or accumulated-exposure-related absence, with a possible persistence or moral-hazard-sensitive margin at longer durations.

For very short-term absence, the result points to a different mechanism. The exploratory plots show that the Netherlands has high one-day absence and high absence frequency, which fits the low short-term reporting threshold in the Dutch framework: there is no formal doctor's note requirement and waiting days are conditional rather than universal. The survival analysis results suggest that only some operational variables help explain short-term Dutch absence. Chilled shifts may plausibly relate to short-term physical complaints or minor illness, for example cold-related discomfort or colds after working in a cold environment. Weekend or Friday-related effects, especially among Shoppers, may point more towards timing-sensitive or discretionary absence behaviour, although these scheduling coefficients should be interpreted cautiously because of overlap and possible multicollinearity between weekday, weekend, and shift-time variables. The suggested absence type for this short-term margin is therefore mixed: partly operationally avoidable absence related to cold-zone preparation, and partly threshold-sensitive or discretionary absence enabled by the low Dutch reporting threshold.

A second Dutch country-specific finding is the positive association between permanent contracts and absence. Since age and tenure are controlled for, this cannot be explained only by permanent employees being older or longer-tenured. Instead, permanent contract status may capture employment security, lower perceived constraints around reporting sick, or Dutch-specific contract allocation practices. This suggests a possible security- or incentive-sensitive absence margin, especially when combined with the low short-term reporting threshold and generous long-term protection.

For logistics, long-term absence should be addressed through workload adaptation, early case management, reintegration support, and attention to older or more established employees. Very short-term absence requires a different response: clearer attendance norms, better monitoring of timing-sensitive absence patterns, local management attention, and practical prevention of avoidable short-term complaints, such as better preparation and clothing for cold-zone work. For policy interpretation, the Dutch case suggests that low short-term barriers may increase very short-term reporting, while generous long-term wage replacement may matter most once age- or recovery-related absence has already started.

For policy, the Dutch case suggests that the same sickness absence framework may create different challenges at different margins. At the very short-term margin, the absence of a formal doctor's note requirement and the conditional nature of waiting days lower the reporting threshold. This may support legitimate recovery, but it also leaves more room for threshold-sensitive or discretionary one-day absence. At the long-term margin, the high effective wage replacement rate and long employer-payment obligation make recovery and reintegration especially important once absence has started. The policy implication is therefore not necessarily that the Netherlands should simply reduce protection, because stricter short-term barriers may also increase presenteeism. Rather, this evidence-base suggests that the high incidence of very short-term absence and persistent sickness cases in the Netherlands is significantly associated, through interactions with operational conditions, with certification requirements, waiting-day arrangements, and financial incentives. These findings provide a strong basis for the Ministry of Social Affairs and Employment to assess whether these policy levers could be used to mitigate problematic absence margins, while carefully considering employees' legitimate recovery needs and the risk of increased presenteeism. An important note is that the relatively low Dutch medium-term absence shows that the Dutch framework does not create uniformly higher absence across all durations.

In **Germany**, two absence margins stand out: short- to medium-term absence and the lower absence rates among older and permanent-contract employees. The exploratory duration plots show relatively high absence during the first weeks of a spell, especially within the period in which wage replacement remains at 100%. At the same time, very short one-day absence is less dominant than in the Netherlands, which fits the German day-one doctor's note requirement for Shoppers and Runners. After the first 42 days, long-term absence becomes less prominent, which is consistent with the reduction in wage replacement after the employer-paid period.

For the short- and medium-term margin, policy is a plausible explanation. Germany combines no waiting days with full wage replacement during the first six weeks, which lowers the financial cost of both reporting sick and remaining absent during this period. The doctor's note requirement may raise the administrative threshold for very short spells, but it does not remove the generous financial incentive during the early part of the absence spell. The suggested absence type is therefore not purely discretionary short-term absence, but rather short- to medium-term absence that is compatible with a generous early wage-replacement system. This may include legitimate recovery absence, but also some incentive-sensitive persistence during the fully compensated period.

The regression results add an important workforce-composition qualification. Older workers and permanent-contract employees in Germany are generally associated with lower absence rates, which differs from the Netherlands and France. This does not mean that age or permanent contracts directly reduce absence. A more plausible interpretation is that these groups represent a more selected, stable, or attached subgroup within a workforce that is otherwise largely fixed-term and heterogeneous. The survival analysis still shows that age can be related to slower return-to-work, but in Germany this does not translate into higher overall absence rates for older workers in the OLS models. Therefore, the German long-term pattern appears less driven by older-worker absence burden than the Dutch pattern. The suggested absence type here is mainly a selection or stability effect, rather than a direct policy or health effect.

Operationally, Germany also shows signs that local context matters, as visualized in exploratory plots in section 4.1 and Appendix H. In the survival models, German Shopper spell duration is related to variables such as people per shift and Captain absence, while exogenous and disruption-related variables are also more visible than in some other countries. This suggests that part of German absence duration may be connected to local site scale, staffing pressure, leadership continuity, shared working conditions, or operational shocks. These findings point more towards avoidable work-related or team-context absence than towards purely individual sickness behaviour. For logistics, the German strategy should therefore focus on local operational diagnosis: onboarding and retention of fixed-term workers, Captain continuity, team support, staffing pressure, and monitoring of medium-duration spells before they become persistent.

Germany's lack of waiting days may make short disruption-related absence less costly, which could amplify the relationship between disruptions and short sickness spells. The survival models show the higher disruption-related absence seems more strongly related to short-term reporting. Even though, this does not increase the absence burden, it might disrupt scheduled operations. Since weather events, operational disturbances and social events like the European Championship should not automatically relate to medical sickness in a direct sense, their association with Runner spells may therefore indicate a avoidable or threshold-sensitive mechanism. This could include stress, perceived work pressure, lower motivation during difficult operational conditions, or timing of short-term absence. For logistics, this points to resilience planning through staffing buffers, clear communication, route and workload distribution, and recovery time during disruptive periods.

For policy, the German case suggests that certification and wage replacement operate at different margins, but wage replacement should not be treated as the only explanation for the short- and medium-term pattern. The doctor's note requirement appears relevant for limiting very short absence, while the 100% wage replacement period may partly explain why absence remains relatively high during the first six weeks. At the same time, the regression results show many significant operational and workforce-related associations in Germany, suggesting that local operational variation also explains part of the observed absence differences. This should be interpreted cautiously because the German dataset contains many observations, so smaller effects are more likely to become statistically significant. The policy implication is therefore that administrative verification seems most relevant at the onset margin, while wage replacement and operational context together shape absence continuation during the first six weeks.

In **France**, the country-specific pattern is defined by a contrast between low very-short-term absence and a more specific tenure-related absence pattern among Shoppers. The exploratory frequency and duration plots show relatively low absence frequency and low very-short-term absence. This aligns with the French institutional framework, where employees face both three waiting days and a doctor's note requirement from the first day. These rules increase the financial and administrative cost of reporting sick and therefore provide a plausible explanation for the low short-term reporting margin. The suggested absence type at this margin is mainly reduced threshold-sensitive or discretionary short-term absence.

However, the French case should not be interpreted simply as a "strict policy, low absence" case. Strict short-term barriers may reduce reported short spells, but they do not necessarily prevent absence once a spell passes the initial reporting threshold. The relatively higher French absence in the 42–182 day range suggests that other mechanisms become more important after onset, such as health severity, workforce composition, role-specific working conditions, recurrence among a smaller group of workers, or location-level factors. The short-term policy barriers may also create a presenteeism risk: some employees may continue working while ill when symptoms are real but not severe enough to justify the financial loss and administrative burden of reporting sick.

The regression results add an important workforce-composition finding. French Shoppers show a strong tenure-related absence pattern in the OLS models, while the survival analysis suggests that this pattern is not mainly driven by longer sickness spells. This means that the higher absence burden among the relevant tenure groups is more likely related to short-term absence or higher absence occurrence than to slower return-to-work. Although French compensation rules include seniority-based top-ups, the policy analysis suggests that only a limited part of the operational workforce qualifies for extensive tenure-based benefits. The tenure result is therefore unlikely to be explained by policy eligibility alone. A more plausible interpretation is that French Shopper absence is related to employee selection, job fit, and workforce attachment.

For logistics, the French priority is therefore not generic absence control, but targeted attention to Shopper workforce development. The findings point towards the importance of talent retention and job-fit monitoring as more relevant levers. For policy interpretation, the French case illustrates the trade-off of strict short-term barriers. Waiting days and certification requirements appear effective in raising the reporting threshold, but this may also discourage legitimate short-term recovery and increase presenteeism. The French system therefore seems strongest at limiting short-term reporting, while medium-duration and tenure-related absence require employer-level prevention and workforce support once absence has passed the initial threshold.

Taken together, SQ3 shows that sickness absence should not be treated as one homogeneous problem. For Dutch logistics operations, the most actionable factors differ between very short-term and long-term absence. Very short-term absence appears related to the low reporting threshold, timing-sensitive patterns such as Friday or weekend effects among Shoppers, and potentially avoidable short-term complaints linked to cold-zone work. This points to operational actions such as clearer attendance norms, closer monitoring of timing-sensitive absence patterns, local management attention, and better cold-zone preparation through clothing, onboarding, and task expectations. Long-term absence is more strongly connected to older and more established employees, and should therefore be addressed through workload adaptation, early case management, reintegration support, and targeted attention to older, permanent, or longer-tenured workers.

From the institutional side, the results suggest that national social-security frameworks mainly shape two margins of sickness absence. Waiting days and doctor's note requirements appear most relevant for the short-term reporting threshold. The French pattern supports this interpretation, because stricter short-term barriers coincide with lower short-term absence and frequency, while the Dutch framework leaves more room for one-day and threshold-sensitive absence. Wage replacement rates and employer-payment duration appear more relevant for absence persistence and return-to-work incentives. Here, Germany provides a useful contrast: its lower long-term tail after the reduction in wage replacement suggests that financial incentives may matter once absence continues, although operational and workforce factors also remain important. The policy implication is therefore not simply to make sick leave stricter, but to distinguish between short-term reporting incentives and long-term reintegration incentives, while avoiding unintended increases in presenteeism.

5 Conclusion and Discussion

This thesis investigated to what extent national social security frameworks, employee factors, job-context factors and exogenous conditions are associated with sickness absence behaviour among logistics workers in the Netherlands, Germany and France. Using a within-firm comparative design within Picnic, the study compared sickness absence across different national institutional regimes while keeping the employer and broad operational context relatively comparable.

5.1 Conclusion

This thesis shows that sickness absence among logistics workers is associated with a combination of national institutional context, employee characteristics, operational conditions, and exogenous factors. These associations differ across countries, job roles, and dimensions of sickness absence, indicating that the occurrence of absence and the duration of sickness spells should not be understood as outcomes of one common mechanism. The findings further suggest that observed absence behaviour reflects not only health-related circumstances, but also differences in employment conditions, work organisation, scheduling exposure, local team context, and the incentives embedded in national sickness absence frameworks.

One of the most important overall insights is that sickness absence should be interpreted as a multidimensional outcome rather than as a direct proxy for illness. Observed absence may reflect legitimate recovery, avoidable work-related absence, discretionary or incentive-sensitive reporting, or, in the opposite direction, presenteeism when employees continue working despite health complaints. This distinction is essential for answering the research question, because the same aggregate absence rate may be produced by different mechanisms. A high absence rate may reflect many short spells, fewer long spells, or a combination of both. Similarly, low absence does not necessarily mean that employees are healthier or that the absence system performs better, because it may also indicate that employees face stronger barriers to reporting sick. The answer to the research question is therefore not that one category of determinants dominates, but that different determinants matter at different absence margins.

The first main conclusion is that national sickness absence policy appears to matter primarily through two margins: the short-term reporting threshold and longer-term absence persistence. These margins must be observed and analyzed separately as they relate to vastly different policy levers and operational determinants. Waiting days and doctor's note requirements appear most relevant for whether employees report very short sickness absence. This is visible in the French pattern, where the combination of waiting days and day-one certification coincides with low very-short-term absence and lower absence frequency. The Dutch pattern provides the contrasting case: the absence of a formal doctor's note requirement and the conditional nature of waiting days leave a lower short-term reporting threshold, which is consistent with higher one-day and very short-term absence. Wage replacement rates and employer-payment duration appear more relevant once absence has started. The Netherlands, with relatively generous long-term protection and long employer-payment obligations, shows the clearest long-duration absence burden. Germany adds nuance: the day-one doctor's note requirement appears relevant for limiting very short absence, while the 100% wage replacement period during the first six weeks is consistent with relatively more short- to medium-term absence before the long-term tail becomes less prominent.

This does not mean that stricter sickness absence rules are automatically better. Higher absence in the Netherlands may indicate more room for threshold-sensitive or avoidable absence, but it may also mean that genuinely sick employees are better protected against working while ill. Likewise, lower short-term absence in France may indicate that waiting days and certification requirements reduce discretionary or avoidable absence, but it may also hide presenteeism. The policy conclusion is therefore not that the Netherlands should simply reduce sick-pay protection. Rather, Dutch policy should distinguish more clearly between short-term reporting incentives and long-term reintegration incentives. Short-term policy levers, such as waiting-day design or verification requirements, mainly affect the threshold for reporting sick. Long-term policy levers, such as wage replacement, employer obligations and reintegration support, mainly affect persistence and return-to-work once absence has started.

The country comparison shows that each national context's dominant absence margins become meaningful when linked to the employee characteristics, operational variables and exogenous factors that structure them. In the Netherlands, sickness absence is concentrated at two separate margins: very short-term absence and long-term absence. The Dutch short-term margin is consistent with the low reporting threshold. At the same time, this margin is also supported by operational timing signals, including Dutch Shopper Friday effects, timing-sensitive scheduling patterns, and short-term cold-zone-related absence. These findings suggest that part of Dutch short-term absence may be threshold-sensitive or operationally avoidable. The long-term Dutch margin is different. It is not simply explained by extensive long-term wage replacement. Rather, once a spell has started, it reflects the interaction between the Dutch framework's long-term mechanisms, and a relatively older and longer-tenured workforce, plus the positive association between permanent contracts and absence. Together, these factors seem to amplify the effect to make return-to-work dynamics more visible in the Dutch absence burden. This increases the overall absence burden and makes absence more persistent and more costly.

Germany shows a different pattern. The exploratory policy analysis suggests that German absence is especially relevant in the early compensated period, where there are no waiting days and wage replacement remains at 100% during the first six weeks. However, the regression results show that this policy explanation is incomplete. German absence is also strongly structured by operational and workforce variables, being people per shift, Captain absence, lateness, performance variation, major operational disruptions, and the selected nature of permanent-contract employees. This means that German sickness absence should be interpreted as a combination of generous early-stage income protection and substantial local operational variation. The German conclusion is therefore that policy may shape the financial conditions for short- and medium-term absence, but the aforementioned variables explain where in operations this absence concentrates.

France provides the clearest example of strict short-term policy barriers, but also shows why low short-term absence should not be treated as the full explanation. Waiting days and day-one certification are consistent with low very-short-term absence and low absence frequency, suggesting that French policy raises the short-term reporting threshold. However, the regression results show a distinct Shopper tenure pattern, while the survival results suggest that this is not mainly driven by longer spells. This points more toward short-term occurrence, a lack of talent retention among French Shoppers than toward policy eligibility or long-duration recovery. The French conclusion is therefore two-sided: strict institutional barriers appear to suppress short-term reporting, but the remaining absence burden is concentrated in specific workforce segments and requires employer-level attention to onboarding and retention.

Across countries, the most important non-policy findings are employee profile, scheduling, team context, and external shocks. Age is the clearest duration-related employee characteristic: older employees generally return to work more slowly, which points mainly toward legitimate recovery and longer recovery needs. Gender is the most consistent absence-rate association, but should be interpreted as a workforce-composition finding rather than as an operational lever. Tenure and contract type are more context-dependent: they do not have one universal meaning, but appear to capture differences in workforce selection and retention. Operationally, the most relevant findings are recent scheduling intensity for Shoppers, Chilled/Frozen shift exposure, Captain absence, local site variation, and disruption sensitivity among Runners. Exogenous factors add further context: influenza is most consistent with a genuine health shock, while economic growth appears more related to absence thresholds. Together, these findings show that logistics' most actionable absence levers are not single variables, but combinations of workforce composition, scheduling exposure, local team context, and return-to-work support.

Taken together, the answer to the main research question is that national social security frameworks, individual characteristics, job-context factors and exogenous conditions are all associated with sickness absence behaviour, but at different margins and with different degrees of interpretability. National policy is most relevant for cross-country differences in short-term reporting thresholds and long-term absence persistence. Employee characteristics such as age, tenure and contract type help explain which workforce groups are more associated with absence, but their meaning differs across countries. Job-context factors such as scheduling intensity, shift type, Captain absence, location and disruptions show that sickness absence is also shaped by behaviour and the organisation of work. Exogenous factors, especially influenza and operational disruptions, provide additional context but do not replace the importance of policy and operational explanations.

5.2 Dutch Policy Recommendations

The main contribution of this thesis lies in the evidence base developed throughout the results chapter and synthesised in the conclusion. The recommendations below should therefore be read as a brief translation of these findings into possible policy and operational directions, rather than as a full implementation plan. Operational recomenndations have been placed in Confidential Annex J, and can not be shown in this version due to company-sensitive data.

The main implication of this thesis is that sickness absence should not be addressed as one uniform problem. The findings suggest that different absence margins are shaped by different mechanisms and therefore require different responses. Operationally, this means that logistics should use absence data as a diagnostic tool rather than as an individual monitoring instrument. Short-term absence frequency and long-term absence duration should therefore be monitored separately through an aggregate dashboard that distinguishes between absence margins and enables comparison across roles, sites, and countries. Such a dashboard would help identify where absence concentrates and which type of absence margin is involved, while keeping interpretation at the group level and avoiding conclusions about individual motivation or legitimacy.

For Dutch policy, at the short-term margin, the absence of a formal doctor's note requirement and the conditional nature of waiting days, a relatively low reporting threshold, appear related to a high Dutch short-term absence. Previous scientific literature and the French social security framework and observed sickness absence assessed in this thesis, indicate that short-term levers could reduce Dutch short-term sickness absence. However, this does not imply that the Netherlands should simply make sickness absence stricter, because stricter rules may also increase presenteeism and discourage legitimate recovery. Therefore, the Ministry of Social Affairs and Employment should reassess if the substantial observed short-term sickness absence in (logistics sector of the) Netherlands aligns well with legitimate recovery. This thesis gives some indication of discretionary, or incentive-sensitive, sickness absence, but before policy adjustment are made this must be more extensively investigated for a larger population.

For the long-term margin, a similar argumentation is valid. Long-term sickness absence appears related to the extensive Dutch long-term wage-continuation framework. These patterns suggest that the Dutch framework may make existing recovery-related and employment-security-related absence dynamics more persistent and more costly once absence has started. This does not imply that the Netherlands should simply reduce long-term sickness protection. Long-term wage continuation has an important protective function for employees with genuine recovery needs. Reducing protection too strongly could increase financial insecurity, premature return-to-work, relapse, or presenteeism. The policy implication is therefore that the Ministry of Social Affairs and Employment should evaluate whether the current long-term framework creates sufficient incentives and support for timely, sustainable reintegration. Rather than focusing only on lowering wage replacement, policy attention should be directed toward earlier case management, stronger reintegration incentives, and clearer shared responsibilities between employer and employee once absence becomes persistent.

5.3 Discussion

This study examined how sickness absence among Picnic's operational workforce is shaped by both national sickness absence institutions and company-level operational conditions. The central insight is that sickness absence should not be interpreted as one homogeneous outcome. Sickness absence behaviour may reflect different absence types at different absence margins, but most importantly seems to be associated to a combination of policy-incentives and health-related, workforce, operational and exogenous factors. Short-term absence is more strongly connected to reporting thresholds, scheduling patterns and local attendance behaviour, while medium- and long-term absence is more closely related to recovery, reintegration, accumulated workload and workforce composition.

Comparison with previous literature The overall findings are consistent with Allegro and Veerman's (1998) conceptualisation of sickness absence as a multidimensional outcome shaped by health, institutional incentives, and organisational context rather than as a direct measure of illness alone (Hensing et al., 1998; Johns, 2010; Kremer & Steenbeek, 2009). More specifically, the results support an absence-threshold perspective in which reporting sick depends not only on health complaints, but also on the financial and administrative costs of absence, including waiting days, wage-replacement arrangements, and certification requirements (Böckerman et al., 2018; Henrekson & Persson, 2004; Palme & Persson, 2020; Ziebarth & Karlsson, 2010). Organisational conditions, including employment security, job demands, scheduling, leadership, work attachment, and local attendance norms, may further influence this threshold (Johns, 2010). The findings also show that these mechanisms differ between absence occurrence and spell duration, supporting previous research that treats absence frequency and duration as distinct processes rather than interchangeable outcomes (Čikeš et al., 2018). The contribution of this thesis is to examine these institutional and organisational mechanisms together for comparable operational roles within one company across three national policy environments, allowing differences to be considered across countries, absence margins, roles, and local operational contexts.

The country patterns broadly support economic research on waiting days, certification requirements, and wage replacement, while showing that these policy levers operate at different absence margins. This distinction has received less attention in studies using aggregate absence measures rather than individual sickness-spell data. Waiting days and certification requirements are expected to reduce short-term absence by increasing the financial or administrative cost of reporting sick (Hartman et al., 2013; Henrekson & Persson, 2004; Pollak, 2015). Consistent with this, France combines low very-short-term absence and lower frequency with three waiting days and day-one certification. The Netherlands shows comparatively high one-day and very-short-term absence, in line with the absence of a formal certification requirement and only conditional waiting days. Germany presents a mixed pattern: day-one certification corresponds with fewer one-day spells, but full wage replacement and no waiting days keep the financial cost of short-term absence low, which may help explain its relatively high overall frequency. Duration patterns also broadly align with research linking extensive wage replacement to greater absence persistence (Böckerman et al., 2018; Palme & Persson, 2020; Ziebarth & Karlsson, 2010). German absence is relatively high during the first six weeks of full wage replacement but has a less pronounced long-term tail after compensation falls, while the Dutch long-term burden is consistent with prolonged wage continuation and employer responsibility. However, the Dutch and French distributions do not support a simple relationship between generosity and duration. Dutch absence is concentrated at very short and long durations, whereas France has substantial absence between 43 and 182 days despite relatively limited statutory replacement. This suggests that results could not be fully explained based on policy-analysis results from previous literature, indicating medium- and long-term absence also depend on health severity, recurrence, workforce composition, role-specific conditions, and local operational context.

The employee-characteristic findings partly align with previous determinant studies, while also confirming that these relationships are highly context-dependent. Older employees generally return to work more slowly, which is consistent with literature linking age to longer sickness spells, even when older workers do not necessarily report sick more frequently (Beemsterboer et al., 2009; Čikeš et al., 2018). At the same time, the association between age and the overall absence rate differs across countries, suggesting that its relevance depends on workforce composition, employment conditions, national institutional context, and the specific absence outcome being examined. Whereas previous studies have mainly examined age and other employee characteristics as direct determinants of sickness absence, this thesis also shows the value of considering how their associations may differ across social security frameworks. This cross- interaction between employee characteristics and institutional context represents an important contribution of the analysis. The generally higher absence associated with female employees is also consistent with previous research, although the available data cannot determine whether this reflects differences in health exposure, care responsibilities, reporting behaviour, or other unobserved factors. Tenure and contract type show less uniform relationships, which similarly matches earlier literature reporting both positive and negative tenure effects and frequently lower absence among employees with less secure contracts (Čikeš et al., 2018). The positive association between permanent contracts and absence in the Netherlands is compatible with the argument that stronger employment security lowers the perceived constraint around reporting sick, whereas the negative German association points more toward selection: permanent German employees may represent a more stable or attached subgroup within an otherwise predominantly fixed-term workforce. Overall, the employee findings support the literature's broader conclusion that age, tenure, gender, and contract type matter, but that their interpretation depends strongly on national workforce structure and employment context.

The operational findings broadly support previous research showing that sickness absence is associated with work scheduling, performance, lateness, leadership, and the scale and organisation of operations (Afsa & Givord, 2013; Bakker & Demerouti, 2007; Bernstrøm & Houkes, 2017; Johns, 2010). However, these relationships are also more difficult to validate consistently than the policy or employee-characteristic findings. Both previous literature and the results of this thesis indicate that operational associations depend strongly on the role, country, location, and workforce context being studied. Scheduling intensity, weekday and shift-time exposure, performance indicators, lateness, Captain absence, and team size were relevant in several models, although their significance differed across roles and countries. The scheduling findings are broadly consistent with Ropponen et al. (2019), who found that long working hours, consecutive night shifts, and short recovery intervals increased the risk of short sickness absence. Turunen et al. (2022) similarly linked less favourable working-hour patterns to higher short-term absence. These studies support the interpretation that work scheduling can affect recovery and absence risk, although they do not directly explain the association with longer Shopper spells found here. The relevance of Captain absence and team context is consistent with Kristensen et al.

(2006), who found that employee absence was strongly related to the absence of the unit manager. Gellatly (1995) also showed that supervisory fairness and group absence norms were associated with employee absence. More broadly, Čikeš et al. (2018) identify scheduling, work-unit size, supervisory behaviour, performance, attendance norms, and organisational commitment as relevant determinants. The performance and lateness findings should nevertheless be interpreted cautiously, as they may reflect underlying differences in motivation.

The exogenous findings are broadly consistent with previous literature. Asfaw et al. (2017) identified substantial absenteeism associated with influenza-like illness and showed that paid sick leave may reduce absence costs by limiting workplace transmission. This supports interpreting the positive influenza association as primarily health-related. The economic-growth finding is consistent with Palme and Persson (2020), who describe sickness absence as procyclical: absence tends to increase when employment is high because less healthy workers enter employment and employees feel more secure reporting sick. Economic growth is nevertheless only an indirect measure of these labour-market mechanisms. The disruption findings are more novel and harder to validate against earlier research because major operational disruptions are rarely included as a distinct explanatory factor in sickness-absence studies. Their stronger relevance for Runners is nevertheless plausible. from a absence-threshold perspective, given their greater exposure to weather, traffic, route conditions, delivery delays, and customer-facing pressure.

Novelty and significance

The main contribution of this thesis is that it brings national sickness absence policy, workforce composition, and operational context together within one empirical analysis. Previous economic research has shown that sickness absence responds to financial incentives, waiting days, certification requirements, and wage replacement (Böckerman et al., 2018; Hartman et al., 2013; Henrekson & Persson, 2004; Palme & Persson, 2020; Pollak, 2015; Ziebarth & Karlsson, 2010), while organisational research has linked absence to work demands, job attachment, leadership, and local working conditions(Beemsterboer et al., 2009; Čikeš et al., 2018; Gellatly, 1995; Johns, 2011; Johns, 2010; Kristensen et al., 2006). This thesis shows that these explanations are complementary rather than competing. National policy shapes the financial and administrative conditions under which employees report sick and remain absent, while workforce and operational characteristics influence how these conditions become visible across employee groups, roles, and locations. The findings therefore provide an integrated evidence base for understanding sickness absence as the outcome of interacting institutional, individual, and organisational mechanisms.

A second contribution is the distinction between different absence margins. By combining exploratory frequency and duration patterns, person-week OLS models, person-level robustness models, and survival analysis, the thesis distinguishes the overall absence burden from the occurrence and duration of sickness spells. This distinction shows that short- and long-term absence should not be interpreted as manifestations of one uniform mechanism. Waiting days and certification requirements are most closely related to the threshold for reporting short spells, whereas wage replacement, employer obligations, workforce composition, and reintegration conditions become more relevant once an absence spell continues. The analyses also demonstrate that the same variable may have a different meaning depending on the outcome considered. Scheduling intensity, for example, is particularly relevant to spell duration, while cold-zone exposure may be associated with lower overall absence without necessarily being irrelevant to short-term complaints.

A third contribution is the comprehensive inclusion of the large selection of workforce-, and operation-specific variables within one labour-intensive logistics setting. Rather than examining only a small number of general work characteristics, this thesis considers scheduling exposure, shift type, recent workload, performance, lateness, team size, Captain absence, commuting distance, location, and major operational disruptions alongside employee and policy factors. This makes it possible to compare the relative relevance of a broad range of operational conditions across Shoppers, Runners, countries, and absence margins. Some variables, such as commuting distance, did not show consistent significant associations, but their inclusion still contributes to a more complete assessment of the operational environment. Major operational disruptions are particularly novel, as their relationship with sickness absence has received limited attention in previous research. The main contribution therefore lies not in identifying one new universal determinant, but in demonstrating how a comprehensive set of organisational variables can be used to identify where and under which operational conditions different forms of sickness absence are concentrated.

The granular scheduling data also reveal an interpretative issue that is less visible in aggregated studies: employees are not randomly distributed across weekdays, shift times, teams, or locations. Recurring schedules with the same colleagues and supervisors cause several operational variables to capture overlapping variation, as reflected in relatively high VIF values. Weekday and shift-time coefficients may therefore partly describe the employees who usually work those schedules rather than the independent effect of the schedule itself. The contribution lies in showing both where absence is concentrated and why selection into schedules and teams must be considered when interpreting operational associations.

Finally, the thesis has practical significance for Picnic and similar labour-intensive employers because it translates these findings into a differentiated evidence base for absence management. Sickness absence should not be treated only as an HR or compliance issue, but also as a workforce-planning and productivity concern. At the same time, the associative findings should not be used to judge the motivation or legitimacy of individual employees. Instead, they support the use of aggregate absence data as a diagnostic instrument. A dashboard that separately tracks short-term frequency and long-term duration across countries, roles, locations, workforce groups, team contexts, and major disruptions would help identify which absence margin is concentrated where. This would enable more targeted and ethically responsible interventions that correspond to the specific institutional, workforce, or operational mechanism involved.

Limitations

Several limitations should be considered when interpreting the findings. First, the analysis is based on registered sickness absence rather than direct measures of health. The data do not include diagnoses, illness severity, medical necessity, recovery needs, motivation, or presenteeism. Consequently, the study cannot directly distinguish between legitimate recovery absence, avoidable work-related absence, discretionary or incentive-sensitive reporting, and working while ill. These categories are interpretative mechanisms inferred from the combined frequency, duration, OLS, and survival patterns, rather than directly observed outcomes. Higher registered absence may therefore reflect either greater behavioural responsiveness or better protection of genuinely sick employees, while lower absence may reflect either less discretionary reporting or greater presenteeism.

Second, the regression results identify associations rather than causal effects. Unobserved employee, team, location, and time-specific factors may influence both the explanatory variables and sickness absence. As a result, significant coefficients may partly capture correlated omitted factors rather than the proposed mechanism itself. Conversely, a lack of significance for an operational variable does not necessarily imply that the broader operational environment is irrelevant; it may also mean that the included measure captures only a limited part of the relevant operational variation. This harms the broader interpretation of the results. The robustness and survival analyses show whether patterns remain visible across alternative specifications, but they do not eliminate omitted-variable bias or establish causality. Adjacently, a limitation is that the large collection of variables included makes for an extensive and specific reference category, which also harms interpretation. Nevertheless, the inclusion of detailed individual-level workforce and operational data represents a substantial improvement over studies based only on aggregated or general work characteristics.

Third, selection is particularly relevant for the operational variables. Employees are not randomly assigned to locations, contract types, Chilled or Frozen shifts, weekend work, or more intensive schedules. Employees exposed to these conditions may differ systematically in availability, experience, physical capacity, work attachment, or employment stability. Associations between operational characteristics and sickness absence may therefore reflect employee selection as well as the working condition itself.

Fourth, several variables are broad proxies rather than direct measures of the proposed mechanisms. Commuting distance does not capture actual travel time, transport mode, or reliability. Captain absence may indicate leadership discontinuity, but may also reflect broader team or site-level pressure. Operational disruptions may capture demand shocks, staffing problems, weather, or planning quality. Similarly, influenza represents population-level epidemic activity rather than individual infection. These variables are useful for identifying relevant contexts, but they do not isolate the specific mechanism underlying an association.

Fifth, multicollinearity limits the interpretation of individual scheduling coefficients. Weekday exposure, weekend work, shift timing, and total recent shifts are partly mechanically related. Individual coefficients may therefore become unstable or change when related variables are included simultaneously. The scheduling results are more appropriately interpreted as broader patterns of work organisation, availability, and workforce segmentation than as evidence that one specific weekday or shift directly affects sickness absence.

Sixth, the explanatory power of the regression models is limited. Sickness absence is influenced by many determinants that are not captured in the available administrative and operational data, such as individual health, psychological well-being, private circumstances, job satisfaction, informal team norms, and perceived reporting thresholds. Moreover, because the analysis is conducted at the highly granular employee-week level, substantial week-to-week variation is expected to remain unexplained. Many short-term fluctuations arise from idiosyncratic events that cannot realistically be captured in organisational data. The limited R^2 values should therefore not be interpreted as model failure, but as evidence that the included variables explain only part of the variation in sickness absence. The models provide a basis for identifying systematic patterns rather than a complete explanation or precise prediction of individual absence behaviour.

Finally, the cross-country comparison should not be interpreted as a pure comparison of national policy effects. Although the within-firm design improves comparability by holding the employer and broad operational model relatively constant, the country workforces differ in age, tenure, contract composition, site structure, operational maturity, and local labour-market conditions. The number of observations also differs substantially, with the larger German sample providing greater statistical power to detect smaller associations. Country differences and statistical significance should therefore be assessed together with effect sizes, consistency across models, and substantive plausibility.

5.4 Research recommendations

Future research could extend this thesis in five directions that directly address the limitations of the current analysis.

First, future research should improve the measurement of health status and the mechanisms underlying registered sickness absence. Administrative records could be linked to employee surveys, occupational-health information where ethically and legally permissible, and structured input from HR professionals and operational managers. These sources could measure health complaints, recovery needs, psychological well-being, household responsibilities, perceived workload, knowledge of sickness absence rules, attendance norms, and pressure to work while ill. Survey questions and measurement methods should remain consistent over time to support reliable year-to-year comparisons. Combining these data with administrative records would help explain currently unobserved group-level variation and provide a stronger basis for distinguishing legitimate recovery absence, avoidable work-related absence, threshold-sensitive reporting, and presenteeism without inferring these mechanisms from absence patterns alone.

Second, future studies should strengthen causal identification. The current results are associative because aforementioned health- and registration factors plus unobserved employee, team, location, and time-specific characteristics may influence both the explanatory variables and sickness absence. Consequently, it cannot be established whether the variation attributed to a particular policy or operational variable reflects that mechanism itself or correlated omitted factors. This limits the strength of the substantive interpretation, even where associations are statistically significant. Policy changes involving waiting days, certification requirements, wage replacement, or reintegration procedures could be evaluated as quasi-natural experiments using difference-in-differences or interrupted time-series designs. Organisational interventions, such as changes in scheduling, onboarding, Captain support, or disruption staffing, could similarly be introduced through phased pilots across comparable locations. Although these approaches would still depend on identifying assumptions, they would provide stronger evidence than the current observational models on whether policy or operational changes affect sickness absence.

Third, future research should examine employee selection into contracts, locations, shifts, and work patterns through workforce segmentation. Dimensionality-reduction methods such as principal component analysis could first be used to summarise correlated characteristics, including availability, tenure, contract type, scheduling intensity, shift timing, performance, and location. Cluster analysis or latent-profile analysis could then identify groups of employees with similar employment and scheduling patterns. Sickness absence could subsequently be compared across these profiles to assess whether observed operational associations are concentrated within particular workforce segments. This would help distinguish differences associated with the working condition itself from differences related to the types of employees who are typically assigned to those conditions, while also reducing instability caused by multicollinearity.

Fourth, future research should replace broad proxies with more direct measures of the proposed mechanisms. Commuting distance could be supplemented with actual travel time, transport mode, and neighborhood characteristics. Captain absence could be combined or improved with more constant team planning, or indicators of leadership continuity, supervisory support, and staffing pressure to be more indicative of its true value. Operational disruptions could be classified according to their cause, severity, workload consequences, and staffing response. Individual health information or more localised infection indicators could also improve the measurement of genuine health shocks compared with population-level influenza activity alone.

Finally, future research should improve cross-country comparability and account more explicitly for differences in statistical power. Data collection should be harmonised across countries so that employee definitions, contract categories, operational indicators, absence registration, and observation periods are measured consistently. The comparison could be repeated once the German and French operations are more mature and the workforce structures are more similar, including more comparable contract and employment arrangements. Balanced-sample analyses, matched workforce comparisons, and models estimated on common employee subgroups could help assess whether country differences remain after compositional differences are reduced. Future studies should also report effect sizes, confidence intervals, and cross-model consistency alongside statistical significance, particularly because the larger German sample makes smaller associations easier to detect.

Appendices

A Variable Operationalization

A.1 Absence Rate OLS – Person-Week Level

Variable	Shopper - Runner Operationalisation
Absence rate	Per week, per person; (0 - 1) The share of planned, contracted, or expected working time lost due to sickness absence in period t (Discrete)
Shift-type	Observed average count per week per cat; Ambient, Chilled, Frozen (during t-1) (Continuous) - **Not in Runner model**
Shift-day	Observed average count per week per cat; Monday, Tuesday, ... (during t-1) (Continuous)
Shift-time	Observed average count per week per cat; Morning, Afternoon, Evening, Night (during t-1) (Continuous)
Contract-type	Dummy per cat; Permanent, Fixed-term (during t) (Boolean)
Tenure	Dummy per cat; Days of tenure 0-187, 188-365, 366-730, 730+ (during t) (Boolean)
Age	Dummy per cat; Years of age 15-25, 26-40, 40+ (during t) (Boolean)
Gender	Female (during t) (Boolean)
Distance-to-work	Dummy per cat; Distance to work in Km 0-2, 2-10, 10+ (during t) (Boolean)
Performance	Picking speed; CU/worked hours (during t-1) (Continuous) - Driving Score (Continuous)
Lates	Lates/work hours (during t-1) (Continuous)
People per shift	Avg. number of people per shift (during t-1) (Discrete)
Absence of Lead	Avg. Absence rate of Lead (during t-1) (Continuous)
Absence of Colleagues	Avg. Absence rate of colleagues at same site (during t-1) (Continuous)
Nat. Influenza Level	Z-score of national influenza level (during t)(Continuous)
Tightness Labour market	% of quarterly economic growth (during t)(Continuous)
Major oper. disruption	Occurrence of Major operational disruption (during t) (Boolean)

A.2 Absence Rate OLS – Person-Level Robustness

Variable	Shopper - Runner Operationalisation
Absence rate	Per person; (0 - 1) The share of planned, contracted, or expected working time lost due to sickness absence in 2024 and 2025 (Discrete)
Shift-type	Observed average count per week per cat; Ambient, Chilled, Frozen (2024 and 2025) (Continuous) - **Not in Runner model**
Shift-day	Observed average count per week per cat; Monday, Tuesday, ... (2024 and 2025) (Continuous)
Shift-time	Observed average count per week per cat; Morning, Afternoon, Evening, Night (2024 and 2025) (Continuous)
Contract-type	(Mode) Dummy per cat; Permanent, Fixed-term (2024 and 2025) (Boolean)
Tenure	(Mode) Dummy per cat; Days of tenure 0-187, 188-365, 366-730, 730+ (2024 and 2025) (Boolean)
Age	(Mode) Dummy per cat; Years of age 15-25, 26-40, 40+ (2024 and 2025) (Boolean)
Gender	Female (2024 and 2025) (Boolean)
Distance-to-work	Avg. Km (2024 and 2025) (Continuous)
Performance	Avg. Picking speed; CU/worked hours (2024 and 2025) (Continuous) - Driving Score (Continuous)
Lates	Avg. Lates/work hours (2024 and 2025) (Continuous)
People per shift	Avg. number of people per shift (2024 and 2025) (Discrete)
Absence of Lead	Avg. Absence rate of Lead (2024 and 2025) (Continuous)
Absence of Colleagues	Avg. Absence rate of colleagues at same site (2024 and 2025) (Continuous)
Nat. Influenza Level	Avg. Z-score of national influenza level (2024 and 2025) (Continuous)
Tightness Labour market	Avg. % of quarterly economic growth (2024 and 2025) (Continuous)
Major oper. disruption	Avg. Occurrence of Major operational disruption (2024 and 2025) (Boolean)

A.3 Survival Analysis

Variable	Shopper - Runner Operationalisation
Absence Duration	Per spell, per person; (1,2,3,...) number of days of absence spell (Discrete)
Shift-type	Observed average count per week per cat; Ambient, Chilled, Frozen (during t-1) (Continuous) - **Not in Runner model**
Shift-day	Observed average count per week per cat; Monday, Tuesday, ... (during t-1) (Continuous)
Shift-time	Observed average count per week per cat; Morning, Afternoon, Evening, Night (during t-1) (Continuous)
Contentment rate	% planned shifts / availability shifts (during t-1) (Continuous)
Contract-type	Dummy per cat; Permanent, Fixed-term (during t) (Boolean)
Tenure	Dummy per cat; Days of tenure 0-187, 188-365, 366-730, 730+ (during t) (Boolean)
Age	Dummy per cat; Years of age 15-25, 26-40, 40+ (during t) (Boolean)
Gender	Male (during t) (Boolean)
Distance-to-work	Km (during t) (Continuous)
Performance	Picking speed; CU/worked hours (during t-1) (Continuous) - Driving Score (Continuous)
Lates	Lates/work hours (during t-1) (Continuous)
People per shift	Avg. number of people per shift (during t-1) (Discrete)
Absence of Lead	Avg. Absence rate of Lead (during t-1) (Continuous)
Absence of Colleagues	Avg. Absence rate of colleagues at same site (during t-1) (Continuous)
Nat. Influenza Level	Z-score of national influenza level (during t)(Continuous)
Tightness Labour market	% of quarterly economic growth (during t)(Continuous)
Major oper. disruption	Occurrence of Major operational disruption (during t) (Boolean)

B Social Security Framework Tables

Table 8: Dutch sickness absence policy and CAO rules in Picnic implementation

Policy dimension	Dutch policy / CAO rule in Picnic implementation	Context
Waiting days	0/2 waiting days	Under the E-commerce CAO, 2 waiting days apply. If the employee has had no sickness absence in the previous 6 months, 0 waiting days apply.
Replacement rate: Day 3–28	Employer pays 70% of wage. Minimum of minimum wage (€14.81) per month.	Under Dutch policy, absence days may still be paid at 70% as long as the monthly salary is not lower than the minimum wage. For longer spells, this translates to employers paying the minimum wage (€14.81), effectively 92.76% of the normal wage.
Replacement rate: Week 4–52	Employer pays 85% of wage. Minimum of minimum wage (€14.81) per month.	Under the E-commerce CAO, with an effective lower bound of about 92.76% where the minimum wage floor binds.
Replacement rate: Week 52–78	Employer pays 85% of wage.	Under the E-commerce CAO, with no lower bound.
Replacement rate: Week 79–104	Employer pays 70%.	Under Dutch policy, no lower bound. After 104 weeks, WIA takes over absence pay.
Spell-linking rule	If a worker recovers and becomes sick again within 4 weeks, the new spell is treated as a continuation of the previous spell.	
Certification requirements	No formal certification requirement such as a doctor's note.	

Table 9: German sickness absence policy rules in Picnic implementation

Policy dimension	**Dutch policy / CAO rule in Picnic implementation**	**Context**
Waiting days	None	-
Replacement rate: Day 1–42	Employer pays 100% of wage	Under German law, absence days must still be paid at 100% of the average monthly wage of the past 12 months.
Replacement rate: Day 43–Week 78	Insurance pays 70% of wage. Capped at 90% of net pay.	Under German law, after 78 weeks the employer no longer has to pay the wage replacement. National obligatory insurance now pays 70% of the average monthly wage of the past 12 months. As this can be higher than 70% of the net wage due to bonuses and overtime, it is capped at 90% of net pay. However, this still amounts to roughly 70% in Picnic's use case. After 78 weeks, the Bundesagentur für Arbeit takes over absence pay based on case-specific assessment.
Spell-linking rule	If a worker recovers and becomes sick again from a different illness or injury, the absence days are counted from 0 again.	
Certification requirements	Under Picnic's implementation, Shoppers and Runners are required to have a doctor's note at the 1st day of absence. Captains and other Leads are required to have a doctor's note at the 3rd day of absence.	
Trial period absence	Under German law, every employee who is in his/her first 4 weeks of employment will receive full 100% wage replacement by insurance instead of the employer.	

Table 10: French sickness absence policy rules in Picnic implementation

Policy dimension	**French policy / CAO rule in Picnic implementation**	**Context**
Waiting days	Three waiting days	Statutory French sickness benefits generally start from day 4. In the Picnic Fulfilment/Hubs blueprint, employer top-up for Ouvriers et Employés starts from day 6, meaning there is also no employer salary-maintenance top-up during the first five days for this group.

Policy dimension	French policy / CAO rule in Picnic implementation	Context
Replacement rate: Day 4–5	Approximately 50% through statutory sickness benefit, if eligible.	For Shoppers and Runners, employer top-up only starts from day 6 upward.
Replacement rate: Day 6–40	50% government + 50% Picnic; if tenure is 36–60 months.	For Shoppers and Runners with less than 36 months seniority, no employer top-up applies. For Shoppers and Runners with 36–60 months seniority, the WRR is 100% from day 6 to day 40. For 60–120 months seniority, the 100% period runs from day 6 to day 70. For 120+ months seniority, it runs from day 6 to day 100.
Replacement rate: Day 41–70	50% government + 25% Picnic; if tenure is 36–60 months.	For Shoppers and Runners with less than 36 months seniority, no employer top-up applies. For 36–60 months seniority, the WRR falls to 75% from day 41 to day 70. For 60–120 months seniority, the 75% period runs from day 71 to day 130. For 120+ months seniority, it runs from day 101 to day 190.
Replacement rate: Day 70+	Ca. 50%; statutory sickness benefits over up to 3 years.	After the Picnic employer top-up period ends, Shoppers and Runners fall back to the statutory sickness-benefit level of approximately 50%, subject to the statutory maximum duration.
Captain schedule	For Agents de maîtrise with 36–60 months seniority, the WRR is 100% from day 1 to day 30 and 75% from day 31 to day 60. For 60–120 months seniority, the 100% period runs from day 1 to day 60 and the 75% period from day 61 to day 120. For 120+ months seniority, the 100% period runs from day 1 to day 90 and the 75% period from day 91 to day 180. This category may include supervisory roles, but the exact mapping to Picnic roles should be verified.	
Lead schedule	For Cadres with 36–60 months seniority, the WRR is 100% from day 1 to day 60 and 75% from day 61 to day 120. For 60–120 months seniority, the 100% period runs from day 1 to day 90 and the 75% period from day 91 to day 180. For 120+ months seniority, the 100% period runs from day 1 to day 120 and the 75% period from day 121 to day 240. This category should be treated as a more senior managerial classification rather than automatically equated with Fulfilment Captains.	

Policy dimension	**French policy / CAO rule in Picnic implementation**	**Context**
Certification requirements	Under Picnic's French implementation, Shoppers and Runners are required to provide a doctor's note from the first day of sickness absence and within 48 hours. Captains and other Leads are required to provide a doctor's note from the third day of sickness absence.	

C Data Sources & NaN Values

The empirical analysis combines several internal Picnic data sources with external contextual indicators. The internal datasets are used to construct three analytical datasets: an employee-week dataset for the main absence-rate OLS models, a person-level aggregated dataset for the robustness OLS models, and an absence-spell dataset for the survival analysis of sickness spell duration. This structure allows sickness absence to be analysed both as an overall absence burden and as a duration process. The dataset combines several internal Picnic data sources with external contextual indicators.

Workday is used as the authoritative source for employee and contract information, as well as for data at the absence-spell level. It provides the start and end dates of sickness absence spells and contains personnel metadata such as employment contract type, role, site or facility assignment, age, and gender. These variables are essential for linking sickness absence outcomes to employee characteristics and contractual conditions.

Kronos is the primary source for shift-level operational data. It contains detailed information on planned shifts, shift timing, shift duration, lateness, role, and other operational shift characteristics. These data are used to construct variables that describe the working conditions faced by employees in a given week.

However, raw Kronos data also contain operational inconsistencies. For example, some shifts may not have been clocked correctly, employees may forget to clock out, or changes may occur during operations without being fully reflected in the schedule. Therefore, Kronos data are cleaned before being used in the analysis. For worked hours and sickness absence hours, Timesheets are used instead of raw Kronos records. Timesheets provide the corrected administrative record of paid worked hours and paid sickness absence hours. This makes them more suitable for constructing the weekly absence-rate outcome used in the OLS models.

Timesheet data are used to construct the weekly absence outcome in the person-week analysis. These records are consistent with Workday absence records but provide the information at the weekly-hours level. This is essential for the OLS analysis, where the dependent variable is measured as the share of expected working time lost to sickness absence in a given week. Workday data, by contrast, are used for the spell-level survival analysis, where the relevant unit of observation is the sickness absence spell rather than the employee-week.

The timesheet data only cover employees with Picnic contracts and do not include employees hired through temporary employment agencies (TAs). This limitation is not expected to strongly affect the main analysis, as the largest share of employees in the Netherlands and Germany, and all employees in France, are employed directly through Picnic contracts. The analysis therefore focuses on Picnic employees rather than TA workers. This focus also improves data quality, since Picnic-contracted employees are more consistently registered across systems such as Kronos and Workday. For TA workers, data extraction is more prone to administrative inconsistencies and missing values because relevant information is partly managed by external agencies rather than directly within Picnic's internal systems. As a result, excluding TA workers reduces missingness and improves consistency across the linked datasets.

External sources were used to account for external shocks that may influence absence behaviour independently of Picnic's internal operations, the dataset is augmented with country-level and time-varying contextual indicators.

Weekly influenza-level data were obtained from the relevant national public-health institutes: the National Institute for Public Health and the Environment in the Netherlands, the Robert Koch Institute in Germany, and Santé publique France in France (RIVM, 2025; Robert Koch Institute, 2025; Santé publique France, 2025).

Second, quarterly real GDP growth was included to control for changes in the broader macroeconomic environment. Country-level data were obtained from the OECD Quarterly National Accounts (2026). Economic growth was used as an indirect proxy for labour-market conditions, which may influence sickness absence through employment security, outside employment opportunities, and workload pressure. Because GDP growth does not directly measure labour-market tightness, the underlying mechanism cannot be identified from this indicator alone.

Third, major operational disruptions were included to capture exceptional events that could temporarily affect Picnic's operational workforce, such as severe weather, road blockades, protests, urban access restrictions, and transport or security disruptions. Relevant events were identified through informal interviews with People Partners, operational analysts, and Fulfilment Centre and Hub leads, and were included when stakeholders reported substantial effects on staffing, accessibility, deliveries, or fulfilment-centre operations. The resulting events were translated into country- and week-specific indicators. Because event selection relied partly on stakeholder judgement, some subjectivity and cross-country variation are unavoidable. Stronger associations in one country may therefore reflect the identification of more relevant events rather than a genuinely larger disruption effect. National public holidays, without transport disruption, were excluded because they are anticipated and form part of regular operational planning; previous research also found no elevated sickness absence on bridging days around public holidays (Leoni & Böheim, 2018). Appendix I provides an overview of the included events.

Sources of NaN's

The planning data and timesheet worked-hours data were combined to construct an employee-week dataset. The purpose of this merge was to link each employee's realised labour exposure, measured through worked hours in the timesheet data, to the planned operational context in which this work took place. For the main employee-week OLS dataset, time-varying operational variables were constructed over the four weeks preceding the focal employee-week. This means that sickness absence in week t is explained using the employee's observed work context in the previous four weeks rather than information from the same week. This lagged structure preserves temporal ordering and reduces the risk that sickness absence in the focal week affects the explanatory variables. However, it also means that missing values can arise when an employee has no observed or matchable work history in the preceding four-week window.

The largest source of missingness is therefore found in the previous-four-week planning-derived variables. These include the number of shifts, weekday shift counts, shift-time counts, shift-type counts for Shoppers, late shifts, and people per shift. In the main OLS dataset, these variables show repeated missingness within each country-role group because they are derived from the same underlying planning-history merge. Missingness in these variables does not necessarily mean that the employee did not belong to the workforce or that their employee record was incomplete. Instead, it indicates that no usable planning history was available for that employee in the relevant preceding four-week window.

In addition to planning-related missing values, some variables were incomplete in the original administrative data. This applies especially to employee background variables such as gender, address and postal code information. Missingness in these variables may arise from differences in administrative registration, incomplete employee records or privacy restrictions.

NaN-handling

Before estimating the regression and survival models, missing values were systematically assessed for each dataset. Separate missing-value overviews were produced for the Shopper and Runner datasets, reporting the number of missing values, percentage missing, number of non-missing observations, and number of unique non-missing values for each variable. An overview of the missing values before NaN-handling per dataset can be found in Appendix I.

The core metrics used to construct the dependent variables did not contain missing values in the final analytical datasets. For the weekly and aggregated OLS datasets, the base variables were worked hours and sickness absence hours. For the survival dataset, the base variables were the absence-spell start and end dates.

For operational exposure variables based on recent work history, missing values were interpreted as indicating that the employee had no observed shifts in the relevant preceding period. Lagged shift-history variables, including weekday, department and time-of-day shift counts, performance, people per shift, late-shift share, captain absence and worked hours, were therefore coded as zero when missing.

This approach was considered preferable to median imputation or complete-case deletion. Median imputation would assign an artificial operational context, such as an average performance level or team size, to employees who had not worked any shifts during the relevant period. Complete-case deletion would remove these employees and could introduce selection bias, because exclusion would be directly related to recent labour exposure. Zero-coding instead preserves the analytical sample and consistently represents the absence of operational exposure. Since these variables do not otherwise take genuine zero values, zero uniquely identifies observations without recent shift history.

A limitation remains that variables such as performance, people per shift and captain absence are conceptually undefined when no shifts were observed, rather than substantively equal to zero. The inclusion of the total number of shifts in the preceding period partly addresses this issue, as observations without recent shifts are separately identified by a shift count of zero.

For the limited missing demographic variables, NaN-values were handled through median imputation. Missing age, tenure, and distance-to-location values were filled using the median within the most relevant available group, usually country-location first, followed by country-level and global medians. After imputing distance to location, commuting-distance categories were derived.

C.1 NaN Tables

Nan-values Overview - OLS dataset

Table 11: Missing values by country and role for the main OLS dataset before NaN handling

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Dataset size						
Number of observations	72,120	53,255	219,072	413,441	32,761	28,517
Employee profile						
Contract category	26 (0.0%)	1 (0.0%)	231 (0.1%)	257 (0.1%)	63 (0.2%)	68 (0.2%)
Gender	0 (0.0%)	71 (0.1%)	2,336 (1.1%)	6,286 (1.5%)	35 (0.1%)	73 (0.3%)
Age	0 (0.0%)	0 (0.0%)	3 (0.0%)	25 (0.0%)	4 (0.0%)	9 (0.0%)
Tenure days	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Postal code	0 (0.0%)	0 (0.0%)	507 (0.2%)	41 (0.0%)	218 (0.7%)	448 (1.6%)
Distance to work						
Distance to location	0 (0.0%)	104 (0.2%)	507 (0.2%)	515 (0.1%)	218 (0.7%)	448 (1.6%)
Scheduling: total volume, previous 4 weeks						
Total shifts in previous 4 weeks	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Paid hours in previous 4 weeks	775 (1.1%)	884 (1.7%)	8,142 (3.7%)	16,377 (4.0%)	2,271 (6.9%)	1,757 (6.2%)
Scheduling: weekday composition, previous 4 weeks						
Monday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Tuesday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Wednesday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Thursday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Friday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Saturday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Sunday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Scheduling: shift time, previous 4 weeks						
Morning shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Afternoon shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Evening shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)

Continued on next page

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Night shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Scheduling: shift type, previous 4 weeks						
Ambient shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Chilled shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Frozen shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Operational/performance						
Picking/replenishing speed	18,546 (25.7%)		33,491 (15.3%)		6,560 (20.0%)	
People per shift	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Driving score		6,278 (11.8%)		90,039 (21.8%)		5,313 (18.6%)
Late shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Leadership/team context						
Captain absence rate previous 4 weeks	157 (0.2%)	60 (0.1%)	17 (0.0%)	6,325 (1.5%)	0 (0.0%)	296 (1.0%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. All scheduling variables refer to the previous four weeks. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset.

NaN-values overview - Robustness OLS dataset

Table 12: Missing values by country and role for the robustness OLS dataset before NaN handling

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Dataset size						
Number of observations	1,479	1,388	9,187	18,046	2,373	1,789
Employee profile						
Contract category	0 (0.0%)	1 (0.1%)	9 (0.1%)	7 (0.0%)	6 (0.3%)	8 (0.4%)
Gender	0 (0.0%)	3 (0.2%)	76 (0.8%)	186 (1.0%)	5 (0.2%)	8 (0.4%)
Age	0 (0.0%)	0 (0.0%)	0 (0.0%)	16 (0.1%)	1 (0.0%)	2 (0.1%)
Tenure days	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Postal code	0 (0.0%)	0 (0.0%)	55 (0.6%)	2 (0.0%)	8 (0.3%)	32 (1.8%)
Distance to work						

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Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Distance to location	0 (0.0%)	6 (0.4%)	55 (0.6%)	11 (0.1%)	8 (0.3%)	32 (1.8%)
Scheduling: weekday composition, total-period averages						
Monday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Tuesday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Wednesday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Thursday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Friday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Saturday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Sunday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Scheduling: shift time, total-period averages						
Morning shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Afternoon shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Evening shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Night shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Scheduling: shift type, total-period averages						
Ambient shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Chilled shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Frozen shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Operational/performance						
Average picking/replenishing speed	149 (10.1%)		90 (1.0%)		49 (2.1%)	
Average people per shift	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Average driving score		55 (4.0%)		1,539 (8.5%)		139 (7.8%)
Average late shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Leadership/team context						
Average captain absence rate	0 (0.0%)	0 (0.0%)	0 (0.0%)	264 (1.5%)	0 (0.0%)	24 (1.3%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset. All scheduling variables in the robustness dataset refer to person-level averages over the full observation period, not previous four-week values.

NaN-values overview - Survival analysis dataset

Table 13: Missing values by country and role for the survival analysis dataset before NaN handling

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Dataset size						
Number of observations	6,402	1,853	43,393	35,760	4,592	1,602
Outcome and required model variables						
Duration of absence spell	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Returned-to-work event	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Employee profile						
Contract type	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Gender	0 (0.0%)	6 (0.3%)	534 (1.2%)	668 (1.9%)	0 (0.0%)	7 (0.4%)
Age	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Tenure at spell start	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Distance to work						
Distance to location	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Scheduling: total volume, previous 4 weeks						
Number of shifts in previous 4 weeks	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: weekday composition, previous 4 weeks						
Monday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Tuesday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Wednesday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Thursday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Friday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Saturday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Sunday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: shift time, previous 4 weeks						
Morning shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Afternoon shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Evening shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Night shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: shift type, previous 4 weeks						
Ambient shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	

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Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Chilled shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Frozen shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Operational/performance						
People per shift in previous 4 weeks	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Picking/replenishing speed in previous 4 weeks	943 (14.7%)		4,857 (11.2%)		539 (11.7%)	
Driving score in previous 4 weeks		125 (6.7%)		3,325 (9.3%)		123 (7.7%)
Late shifts in previous 4 weeks	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Leadership/team context						
Lead absence rate previous 4 weeks	15 (0.2%)	0 (0.0%)	1 (0.0%)	928 (2.6%)	4,592 (100.0%)	1,602 (100.0%)
Exogenous controls						
Influenza incidence	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Economic growth	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Major operational disruptions	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset. All scheduling variables refer to the previous four weeks.

D Major Operational Disruptions

Table 34 provides an overview of the major operational disruptions included in the analysis. Disruptions were identified based on internal operational knowledge and included only when they were considered sufficiently substantial to potentially affect normal operations. National public holidays were excluded.

Table 14: Overview of major operational disruptions

Country	Operational disruption	Event period
The Netherlands		
NL	Snow and icy conditions; nationwide	16–19 January 2024
NL	Snow and icy conditions; Arnhem region	22 November 2024
NL	Storm Darragh; nationwide	6 December 2024
NL	NATO Summit and associated security and traffic restrictions; The Hague, Rotterdam and Leiden	22–26 June 2025
NL	SAIL Amsterdam; Amsterdam	20–24 August 2025
NL	Carnival; North Brabant and Limburg	10–13 February 2024
NL	Carnival; North Brabant and Limburg	1–4 March 2025
Germany		
DE	Farmers' protests; nationwide	8–15 January 2024
DE	Farmers' protests; Hamburg	29–30 January 2024
DE	Carnival; West & South Germany	10–13 February 2024
DE	Carnival; West & South Germany	1–4 March 2025
DE	UEFA European Football Championship; affected German host-city operations	14 June–14 July 2024
France		
FR	Farmers' protests; Paris	29 January–1 February 2024
FR	Paris Olympic and Paralympic Games and associated transport and security restrictions; Paris	15 July–8 September 2024
FR	Storm Kirk; Paris	9–10 October 2024
FR	"Bloquons tout" protests; nationwide	10 September 2025
FR	Nationwide strike	18 September 2025

Notes: Locations indicate the principal operational areas affected. National public holidays were excluded.

E Descriptive Tables

Absence rate OLS - Person-week level

Table 15: Descriptive statistics by country and role for the main OLS dataset

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Employee profile						
Fixed-term contract	0.496 (0.500)	0.336 (0.472)	0.921 (0.270)	0.972 (0.164)		
Permanent contract	0.503 (0.500)	0.664 (0.472)	0.078 (0.268)	0.027 (0.162)	1.000 (0.044)	1.000 (0.049)
Male	0.587 (0.492)	0.812 (0.391)	0.737 (0.440)	0.888 (0.316)	0.587 (0.492)	0.724 (0.447)
Female	0.413 (0.492)	0.188 (0.391)	0.263 (0.440)	0.112 (0.316)	0.413 (0.492)	0.276 (0.447)
Age under 26	0.179 (0.384)	0.640 (0.480)	0.347 (0.476)	0.591 (0.492)	0.510 (0.500)	0.667 (0.471)
Age 26–40	0.426 (0.494)	0.242 (0.428)	0.484 (0.500)	0.322 (0.467)	0.350 (0.477)	0.300 (0.458)
Age 40+	0.395 (0.489)	0.119 (0.323)	0.170 (0.375)	0.087 (0.281)	0.140 (0.347)	0.033 (0.178)
Tenure 0–93 days	0.021 (0.143)	0.017 (0.129)	0.673 (0.469)	0.700 (0.458)	0.825 (0.380)	0.776 (0.417)
Tenure 94–187 days	0.018 (0.133)	0.027 (0.162)	0.171 (0.377)	0.168 (0.374)	0.096 (0.295)	0.137 (0.344)
Tenure 188–365 days	0.068 (0.252)	0.041 (0.198)	0.093 (0.290)	0.100 (0.300)	0.053 (0.224)	0.063 (0.243)
Tenure 366–730 days	0.397 (0.489)	0.115 (0.319)	0.049 (0.216)	0.029 (0.168)	0.022 (0.147)	0.021 (0.143)
Tenure 731–1095 days	0.328 (0.469)	0.587 (0.492)	0.009 (0.094)	0.003 (0.055)	0.004 (0.063)	0.002 (0.045)
Tenure 1096–1460 days	0.053 (0.224)	0.115 (0.319)	0.002 (0.045)	0.000 (0.000)	0.000 (0.000)	0.001 (0.032)
Tenure 1461+ days	0.115 (0.319)	0.098 (0.297)	0.003 (0.055)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Distance to work						
Walking distance	0.098 (0.298)	0.368 (0.482)	0.157 (0.364)	0.256 (0.436)	0.026 (0.160)	0.211 (0.408)
Biking distance	0.424 (0.494)	0.511 (0.500)	0.444 (0.497)	0.572 (0.495)	0.374 (0.484)	0.579 (0.494)
Driving distance	0.478 (0.500)	0.121 (0.326)	0.399 (0.490)	0.172 (0.378)	0.600 (0.490)	0.210 (0.407)
Scheduling: total volume						
Total shifts in previous week	2.624 (1.799)	5.136 (3.592)	3.251 (1.664)	3.141 (2.427)	3.867 (1.846)	5.281 (3.856)
Paid hours in previous week	25.951 (11.458)	14.593 (9.373)	24.531 (11.055)	10.314 (5.841)	25.517 (12.881)	15.389 (9.086)
Scheduling: weekday composition						
Monday shifts	0.420 (0.422)	0.915 (1.006)	0.563 (0.378)	0.456 (0.575)	0.648 (0.393)	0.961 (0.984)
Tuesday shifts	0.386 (0.408)	0.776 (0.958)	0.533 (0.383)	0.570 (0.638)	0.625 (0.391)	0.889 (0.901)

Continued on next page

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Wednesday shifts	0.334 (0.386)	0.697 (0.918)	0.530 (0.383)	0.483 (0.581)	0.583 (0.387)	0.774 (0.832)
Thursday shifts	0.443 (0.420)	0.691 (0.884)	0.577 (0.373)	0.493 (0.578)	0.677 (0.386)	0.793 (0.837)
Friday shifts	0.450 (0.425)	0.888 (0.937)	0.597 (0.376)	0.584 (0.637)	0.738 (0.381)	1.043 (0.958)
Saturday shifts	0.307 (0.384)	0.574 (0.825)	0.449 (0.338)	0.555 (0.618)	0.593 (0.362)	0.807 (0.780)
Sunday shifts	0.284 (0.380)	0.597 (0.875)	0.002 (0.024)	0.000 (0.001)	0.002 (0.023)	0.014 (0.121)
Scheduling: shift time						
Morning shifts	1.644 (1.902)	0.950 (1.291)	2.041 (1.720)	0.325 (0.611)	2.896 (1.806)	0.165 (0.441)
Afternoon shifts	0.942 (1.584)	2.049 (1.798)	1.155 (1.366)	1.169 (1.265)	0.971 (1.246)	2.046 (1.614)
Evening shifts	0.038 (0.228)	2.079 (2.153)	0.055 (0.427)	1.619 (1.452)	0.000 (0.044)	3.061 (2.453)
Night shifts	0.000 (0.000)	0.058 (0.164)	0.000 (0.003)	0.028 (0.120)	0.000 (0.000)	0.009 (0.060)
Scheduling: shift type						
Ambient shifts	1.508 (1.434)		2.071 (1.519)		2.275 (1.579)	
Chilled shifts	1.179 (1.233)		1.267 (1.252)		1.658 (1.351)	
Frozen shifts	0.189 (0.515)		0.180 (0.616)		0.220 (0.590)	
Operational/performance						
Driving score		91.977 (4.312)		91.321 (5.416)		89.613 (4.644)
Picking/replenishing speed	12.184 (17.935)		9.318 (10.859)		8.542 (6.988)	
Late shifts	0.102 (0.403)	0.247 (0.442)	0.415 (0.705)	0.188 (0.377)	0.392 (0.677)	0.615 (0.671)
People per shift	55.858 (40.661)		76.873 (47.945)		71.739 (47.846)	
Leadership/team context						
Captain absence rate previous 4 weeks	0.064 (0.039)	0.050 (0.084)	0.082 (0.042)	0.048 (0.061)	0.065 (0.045)	0.039 (0.088)
Average captain absence rate	0.064 (0.024)	0.049 (0.052)	0.085 (0.024)	0.048 (0.022)	0.058 (0.022)	0.039 (0.034)
Exogenous controls						
Influenza incidence	-0.263 (0.729)	-0.272 (0.720)	0.217 (1.198)	0.203 (1.190)	0.214 (0.990)	0.267 (0.993)
Economic growth	0.151 (0.139)	0.147 (0.142)	-0.033 (0.047)	-0.030 (0.046)	0.066 (0.074)	0.051 (0.061)
Major operational disruptions	0.057 (0.231)	0.059 (0.236)	0.018 (0.132)	0.015 (0.120)	0.078 (0.268)	0.070 (0.255)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country.

Absence rate OLS Robustness - Person level Robustness OLS Dataset

Table 16: Descriptive statistics by country and role for the robustness OLS dataset

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Employee profile						
Fixed-term contract	0.696 (0.460)	0.445 (0.497)	0.983 (0.131)	0.994 (0.075)	0.003 (0.050)	0.004 (0.067)
Permanent contract	0.304 (0.460)	0.555 (0.497)	0.017 (0.131)	0.006 (0.075)	0.997 (0.050)	0.996 (0.067)
Male	0.587 (0.493)	0.814 (0.389)	0.744 (0.437)	0.868 (0.339)	0.625 (0.484)	0.731 (0.443)
Female	0.406 (0.491)	0.184 (0.387)	0.253 (0.435)	0.129 (0.335)	0.375 (0.484)	0.269 (0.443)
Age under 26	0.266 (0.442)	0.710 (0.454)	0.449 (0.497)	0.656 (0.475)	0.596 (0.491)	0.695 (0.461)
Age 26–40	0.429 (0.495)	0.207 (0.406)	0.426 (0.495)	0.280 (0.449)	0.306 (0.461)	0.276 (0.447)
Age 40+	0.306 (0.461)	0.082 (0.275)	0.125 (0.331)	0.065 (0.246)	0.099 (0.298)	0.029 (0.168)
Tenure 0–93 days	0.021 (0.143)	0.017 (0.130)	0.665 (0.472)	0.691 (0.462)	0.785 (0.411)	0.732 (0.443)
Tenure 94–187 days	0.018 (0.131)	0.027 (0.161)	0.169 (0.375)	0.166 (0.372)	0.091 (0.288)	0.129 (0.335)
Tenure 188–365 days	0.068 (0.251)	0.041 (0.199)	0.092 (0.289)	0.099 (0.299)	0.050 (0.218)	0.059 (0.235)
Tenure 366–730 days	0.398 (0.490)	0.115 (0.319)	0.048 (0.215)	0.028 (0.166)	0.021 (0.142)	0.020 (0.139)
Tenure 731–1095 days	0.329 (0.470)	0.588 (0.492)	0.009 (0.093)	0.003 (0.058)	0.004 (0.061)	0.002 (0.041)
Tenure 1096–1460 days	0.053 (0.224)	0.115 (0.319)	0.002 (0.044)	0.000 (0.011)	0.000 (0.021)	0.001 (0.024)
Tenure 1461+ days	0.115 (0.319)	0.098 (0.297)	0.003 (0.051)	0.000 (0.015)	0.000 (0.000)	0.000 (0.000)
Distance to work						
Walking distance	0.114 (0.318)	0.389 (0.488)	0.143 (0.350)	0.238 (0.426)	0.047 (0.211)	0.199 (0.399)
Biking distance	0.430 (0.495)	0.493 (0.500)	0.441 (0.496)	0.576 (0.494)	0.300 (0.458)	0.586 (0.493)
Driving distance	0.456 (0.498)	0.118 (0.323)	0.416 (0.493)	0.186 (0.389)	0.653 (0.476)	0.215 (0.411)
Scheduling: total volume						
Total shifts per week	3.269 (1.136)	5.113 (2.809)	3.714 (0.982)	3.774 (1.755)	4.289 (0.845)	5.617 (2.624)
Average paid hours per week	24.065 (10.122)	12.754 (7.818)	21.133 (9.211)	9.857 (4.713)	23.274 (8.400)	14.377 (6.269)
Scheduling: weekday composition						
Monday shifts	0.463 (0.367)	0.872 (0.862)	0.654 (0.249)	0.554 (0.497)	0.717 (0.315)	0.940 (0.799)
Tuesday shifts	0.436 (0.358)	0.761 (0.821)	0.604 (0.273)	0.666 (0.538)	0.673 (0.319)	0.887 (0.745)
Wednesday shifts	0.373 (0.334)	0.653 (0.751)	0.601 (0.281)	0.547 (0.482)	0.606 (0.319)	0.761 (0.679)
Thursday shifts	0.488 (0.357)	0.632 (0.719)	0.644 (0.260)	0.528 (0.466)	0.728 (0.312)	0.747 (0.681)
Friday shifts	0.497 (0.359)	0.807 (0.770)	0.657 (0.257)	0.611 (0.503)	0.809 (0.273)	1.025 (0.791)
Saturday shifts	0.355 (0.343)	0.563 (0.728)	0.522 (0.237)	0.576 (0.481)	0.664 (0.300)	0.800 (0.655)

Continued on next page

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Sunday shifts	0.335 (0.349)	0.623 (0.785)	0.002 (0.021)	0.000 (0.000)	0.003 (0.034)	0.024 (0.131)
Scheduling: shift time						
Morning shifts	1.774 (1.814)	0.888 (1.124)	2.304 (1.329)	0.317 (0.500)	3.171 (1.344)	0.154 (0.370)
Afternoon shifts	1.115 (1.563)	1.938 (1.497)	1.330 (1.089)	1.324 (1.081)	1.029 (1.049)	2.032 (1.292)
Evening shifts	0.058 (0.238)	2.024 (1.799)	0.052 (0.389)	1.811 (1.186)	0.000 (0.000)	2.987 (1.896)
Night shifts	0.000 (0.000)	0.060 (0.121)	0.000 (0.001)	0.031 (0.101)	0.000 (0.000)	0.010 (0.057)
Scheduling: shift type						
Ambient shifts	1.651 (1.199)		2.116 (1.116)		2.543 (1.068)	
Chilled shifts	1.231 (1.011)		1.025 (0.897)		1.472 (0.948)	
Frozen shifts	0.222 (0.477)		0.103 (0.387)		0.110 (0.277)	
Operational/performance						
Driving score		91.652 (4.443)		90.542 (6.848)		89.111 (4.703)
Picking/replenishing speed	14.341 (19.992)	0.000 (0.002)	9.389 (7.810)	0.009 (0.384)	8.678 (5.421)	0.000 (0.000)
People per shift	65.418 (33.232)	0.989 (0.308)	91.795 (34.892)	1.017 (2.861)	95.999 (36.273)	0.928 (0.275)
Late shifts	0.139 (0.363)	0.256 (0.339)	0.532 (0.625)	0.225 (0.308)	0.722 (0.739)	0.723 (0.554)
Leadership/team context						
Average captain absence rate	0.063 (0.024)	0.047 (0.052)	0.083 (0.023)	0.048 (0.024)	0.061 (0.022)	0.036 (0.034)
Exogenous controls						
Influenza incidence	-0.190 (0.387)	-0.204 (0.405)	0.325 (0.886)	0.224 (0.740)	0.222 (0.792)	0.302 (0.754)
Economic growth	0.159 (0.046)	0.156 (0.055)	-0.038 (0.043)	-0.037 (0.044)	0.066 (0.070)	0.052 (0.056)
Major operational disruptions	0.057 (0.053)	0.059 (0.063)	0.025 (0.093)	0.023 (0.092)	0.061 (0.154)	0.080 (0.182)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country. Outcome and exposure variables are excluded.

Survival Analysis Dataset

Table 17: Descriptive statistics by country and role

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Employee profile						
Temporary/flexible contract	0.726 (0.446)	0.547 (0.498)	0.973 (0.163)	0.995 (0.073)		
Permanent contract	0.274 (0.446)	0.453 (0.498)	0.027 (0.163)	0.005 (0.073)	1.000 (0.000)	1.000 (0.000)
Male	0.640 (0.480)	0.793 (0.405)	0.767 (0.423)	0.892 (0.311)	0.561 (0.496)	0.633 (0.482)
Female	0.360 (0.480)	0.207 (0.405)	0.233 (0.423)	0.108 (0.311)	0.439 (0.496)	0.367 (0.482)
Age under 26	0.237 (0.425)	0.640 (0.480)	0.469 (0.499)	0.645 (0.478)	0.581 (0.493)	0.682 (0.466)
Age 26–40	0.510 (0.500)	0.258 (0.438)	0.429 (0.495)	0.298 (0.457)	0.333 (0.471)	0.297 (0.457)
Age 40+	0.253 (0.435)	0.101 (0.302)	0.102 (0.302)	0.056 (0.231)	0.086 (0.281)	0.021 (0.142)
Tenure 0–93 days	0.010 (0.097)	0.017 (0.128)	0.461 (0.499)	0.381 (0.486)	0.426 (0.495)	0.382 (0.486)
Tenure 94–187 days	0.013 (0.114)	0.017 (0.130)	0.192 (0.393)	0.245 (0.430)	0.231 (0.422)	0.267 (0.442)
Tenure 188–365 days	0.053 (0.225)	0.049 (0.216)	0.194 (0.396)	0.230 (0.421)	0.208 (0.406)	0.245 (0.430)
Tenure 366–730 days	0.304 (0.460)	0.129 (0.335)	0.114 (0.318)	0.129 (0.335)	0.115 (0.319)	0.088 (0.283)
Tenure 731–1095 days	0.326 (0.469)	0.442 (0.497)	0.026 (0.159)	0.013 (0.113)	0.016 (0.126)	0.014 (0.119)
Tenure 1096–1460 days	0.118 (0.323)	0.203 (0.403)	0.005 (0.074)	0.001 (0.037)	0.004 (0.061)	0.004 (0.061)
Tenure 1461+ days	0.176 (0.380)	0.142 (0.350)	0.008 (0.087)	0.000 (0.016)	0.000 (0.000)	0.001 (0.025)
Distance to work						
Walking distance	0.093 (0.291)	0.373 (0.484)	0.156 (0.363)	0.253 (0.435)	0.034 (0.181)	0.240 (0.427)
Biking distance	0.448 (0.497)	0.513 (0.500)	0.458 (0.498)	0.574 (0.495)	0.371 (0.483)	0.529 (0.499)
Driving distance	0.459 (0.498)	0.114 (0.318)	0.386 (0.487)	0.173 (0.379)	0.595 (0.491)	0.230 (0.421)
Scheduling: total volume						
Number of shifts per week	3.123 (1.602)	6.144 (3.736)	3.583 (1.449)	3.676 (2.323)	4.364 (1.326)	6.662 (3.737)
Scheduling: weekday composition						
Monday shifts	0.471 (0.424)	1.172 (1.088)	0.602 (0.380)	0.580 (0.660)	0.729 (0.346)	1.338 (1.059)
Tuesday shifts	0.454 (0.420)	0.990 (1.041)	0.586 (0.383)	0.715 (0.707)	0.722 (0.340)	1.206 (0.960)
Wednesday shifts	0.407 (0.406)	0.868 (1.001)	0.587 (0.386)	0.580 (0.650)	0.657 (0.359)	1.004 (0.927)
Thursday shifts	0.545 (0.419)	0.873 (0.966)	0.649 (0.365)	0.576 (0.635)	0.752 (0.336)	1.009 (0.894)
Friday shifts	0.557 (0.424)	1.047 (0.993)	0.653 (0.368)	0.648 (0.678)	0.827 (0.301)	1.283 (0.977)
Saturday shifts	0.354 (0.405)	0.588 (0.845)	0.500 (0.364)	0.577 (0.641)	0.677 (0.334)	0.815 (0.775)
Sunday shifts	0.334 (0.404)	0.606 (0.886)	0.005 (0.071)	0.000 (0.000)	0.001 (0.019)	0.006 (0.071)

Continued on next page

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Scheduling: shift time						
Morning shifts	1.929 (1.944)	1.119 (1.388)	2.319 (1.698)	0.370 (0.657)	3.311 (1.602)	0.161 (0.422)
Afternoon shifts	1.144 (1.721)	2.531 (1.945)	1.211 (1.381)	1.404 (1.321)	1.053 (1.290)	2.505 (1.545)
Evening shifts	0.050 (0.266)	2.422 (2.246)	0.053 (0.419)	1.868 (1.438)	0.000 (0.000)	3.982 (2.491)
Night shifts	0.000 (0.000)	0.072 (0.209)	0.000 (0.000)	0.035 (0.159)	0.000 (0.000)	0.014 (0.091)
Scheduling: shift type						
Ambient shifts	1.625 (1.352)		2.020 (1.397)		2.232 (1.285)	
Chilled shifts	1.102 (1.141)		1.112 (1.133)		1.685 (1.195)	
Frozen shifts	0.173 (0.503)		0.130 (0.493)		0.207 (0.535)	
Operational/performance						
People per shift	64.144 (36.973)		84.979 (44.952)		79.583 (42.272)	
Picking/replenishing speed	11.837 (21.337)		9.749 (14.952)		9.501 (10.595)	
Driving score		91.798 (4.524)		90.932 (5.422)		88.912 (5.168)
Late shifts	0.125 (0.396)	0.285 (0.494)	0.540 (0.798)	0.218 (0.423)	0.468 (0.715)	0.653 (0.675)
Leadership/team context						
Lead absence rate	0.065 (0.041)	0.050 (0.089)	0.083 (0.042)	0.050 (0.068)	0.079 (0.000)	0.027 (0.000)
Exogenous controls						
Influenza incidence	-0.220 (0.776)	-0.160 (0.810)	0.280 (1.231)	0.295 (1.297)	0.176 (1.007)	0.331 (1.116)
Economic growth	0.146 (0.138)	0.142 (0.151)	-0.030 (0.046)	-0.028 (0.045)	0.071 (0.076)	0.060 (0.069)
Major operational disruptions	0.055 (0.228)	0.058 (0.234)	0.026 (0.160)	0.017 (0.128)	0.075 (0.263)	0.067 (0.251)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country.

F Absence Expectation Distribution Plots

NL:

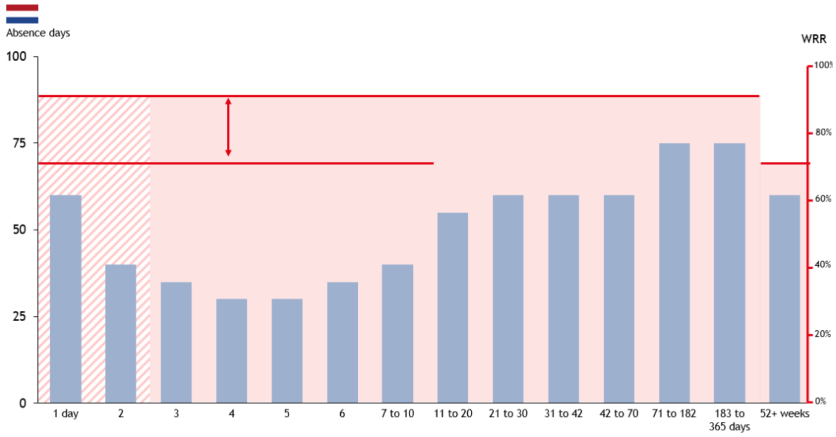

Figure 7: Visual element from the original thesis draft, source page 57.

DE:

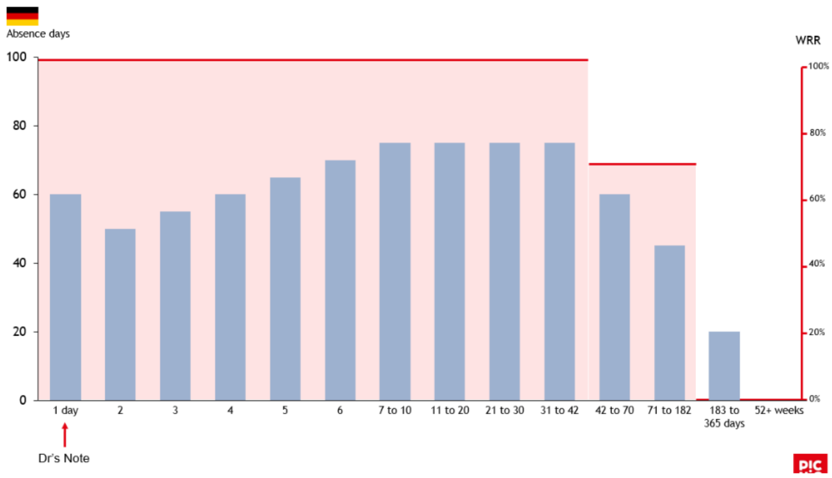

Figure 8: Visual element from the original thesis draft, source page 62.

FR:

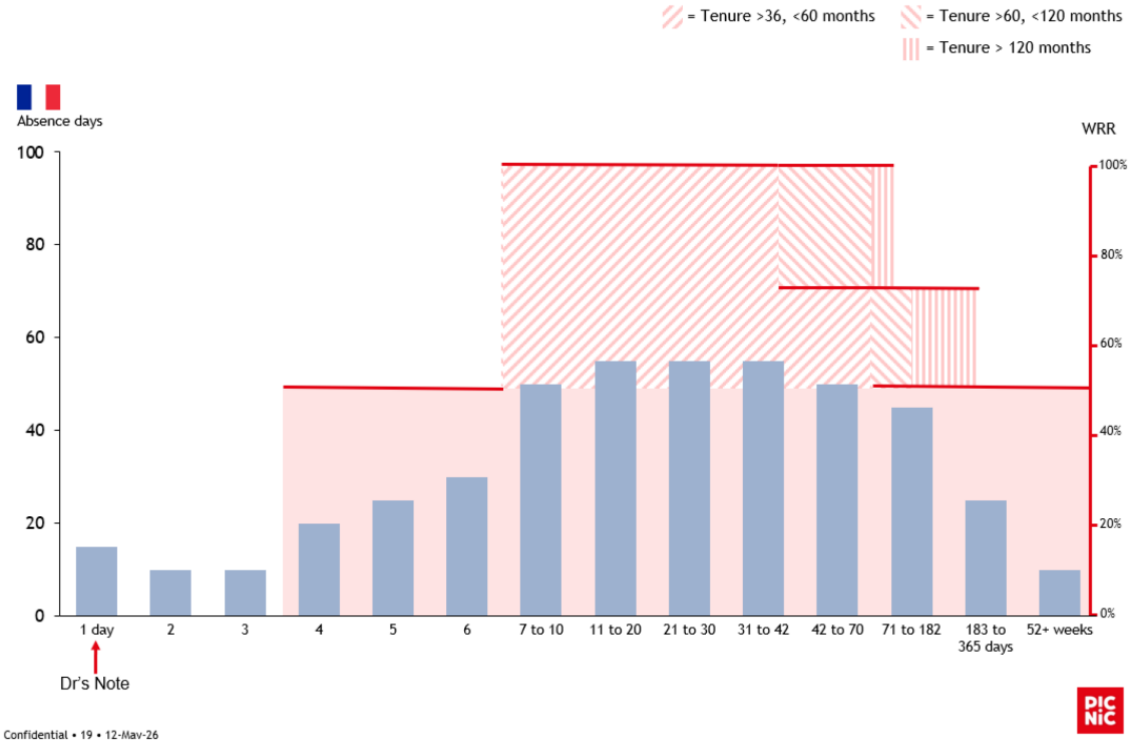

Figure 9: Visual element from the original thesis draft, source page 66.

G OLS Correlation Matrices

Table 18: Correlation heatmap for NL Shopper

	Abs. rate	Fixed-term	Permanent	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Pick/repl. speed	Late shifts	People/shift	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	-0.14	0.14	-0.04	0.04	-0.04	-0.00	0.04	-0.01	-0.01	-0.04	-0.08	0.10	0.01	-0.00	-0.00	-0.28	-0.40	–	-0.07	-0.05	-0.26	0.03	0.01	0.01	0.01	-0.00
Fixed-term	-0.14	1.00	-1.00	0.03	-0.03	0.20	-0.00	-0.15	0.09	0.11	0.23	0.42	-0.54	-0.01	0.02	-0.01	0.17	0.06	–	0.10	0.01	0.15	-0.00	0.01	0.03	0.00	0.00
Permanent	0.14	-1.00	1.00	-0.03	0.03	-0.20	0.01	0.15	-0.09	-0.11	-0.23	-0.42	0.54	0.01	-0.02	0.01	-0.17	-0.05	–	-0.10	-0.01	-0.15	0.00	-0.01	-0.03	-0.00	-0.00
Male	-0.04	0.03	-0.03	1.00	-1.00	0.08	0.00	-0.07	0.01	0.01	-0.00	-0.00	-0.00	-0.02	0.03	-0.02	0.02	0.08	–	-0.17	-0.02	-0.04	0.10	0.16	0.00	-0.01	0.00
Female	0.04	-0.03	0.03	-1.00	1.00	-0.08	-0.00	0.07	-0.01	-0.01	0.00	0.00	0.00	0.02	-0.03	0.02	-0.02	-0.08	–	0.17	0.02	0.04	-0.10	-0.16	-0.00	0.01	-0.00
Age <26	-0.04	0.20	-0.20	0.08	-0.08	1.00	-0.40	-0.38	0.02	0.02	0.02	0.08	-0.10	0.08	0.05	-0.09	-0.05	-0.19	–	0.01	-0.01	0.06	-0.02	-0.03	0.00	0.00	0.00
Age 26–40	-0.00	-0.00	0.01	0.00	-0.00	-0.40	1.00	-0.70	-0.01	-0.02	0.03	0.02	-0.03	-0.04	0.07	-0.05	0.03	0.10	–	-0.00	0.03	-0.02	0.00	0.00	0.01	0.00	-0.00
Age 40+	0.04	-0.15	0.15	-0.07	0.07	-0.38	-0.70	1.00	-0.00	0.00	-0.05	-0.09	0.11	-0.02	-0.11	0.12	0.01	0.06	–	-0.01	-0.02	-0.02	0.01	0.02	-0.01	-0.01	0.00
Tenure 0–93	-0.01	0.09	-0.09	0.01	-0.01	0.02	-0.01	-0.00	1.00	-0.01	-0.02	-0.06	-0.12	-0.02	-0.00	0.01	0.02	-0.01	–	0.00	0.01	0.03	0.02	0.02	0.04	0.02	0.01
Tenure 94–187	-0.01	0.11	-0.11	0.01	-0.01	0.02	-0.02	0.00	-0.01	1.00	-0.03	-0.07	-0.14	-0.01	-0.00	0.00	0.03	0.00	–	-0.01	0.00	0.05	-0.00	0.01	0.04	0.01	-0.01
Tenure 188–365	-0.04	0.23	-0.23	-0.00	0.00	0.02	0.03	-0.05	-0.02	-0.03	1.00	-0.15	-0.30	-0.02	0.01	-0.00	0.07	0.06	–	0.02	-0.00	0.06	0.00	0.02	-0.01	0.02	-0.02
Tenure 366–730	-0.08	0.42	-0.42	-0.00	0.00	0.08	0.02	-0.09	-0.06	-0.07	-0.15	1.00	-0.85	-0.01	0.02	-0.01	0.13	0.06	–	0.03	0.00	0.08	-0.02	-0.01	0.00	0.02	0.00
Tenure 731+	0.10	-0.54	0.54	-0.00	0.00	-0.10	-0.03	0.11	-0.12	-0.14	-0.30	-0.85	1.00	0.02	-0.03	0.01	-0.17	-0.08	–	-0.04	-0.00	-0.12	0.01	-0.01	-0.01	-0.03	0.01
Walking dist.	0.01	-0.01	0.01	-0.02	0.02	0.08	-0.04	-0.02	-0.02	-0.01	-0.02	-0.01	0.02	1.00	-0.28	-0.32	-0.08	-0.06	–	-0.00	-0.03	-0.02	-0.03	-0.03	0.00	0.01	-0.00
Biking dist.	-0.00	0.02	-0.02	0.03	-0.03	0.05	0.07	-0.11	-0.00	-0.00	0.01	0.02	-0.03	-0.28	1.00	-0.82	-0.02	-0.06	–	-0.03	-0.02	0.05	-0.08	-0.13	0.00	-0.01	-0.00
Driving dist.	-0.00	-0.01	0.01	-0.02	0.02	-0.09	-0.05	0.12	0.01	0.00	-0.00	-0.01	0.01	-0.32	-0.82	1.00	0.07	0.10	–	0.03	0.04	-0.04	0.09	0.14	-0.00	0.00	0.00
Shifts prev. week	-0.28	0.17	-0.17	0.02	-0.02	-0.05	0.03	0.01	0.02	0.03	0.07	0.13	-0.17	-0.08	-0.02	0.07	1.00	0.50	–	0.11	0.16	0.65	-0.14	-0.22	0.00	-0.04	-0.01
Paid hours prev. week	-0.40	0.06	-0.05	0.08	-0.08	-0.19	0.10	0.06	-0.01	0.00	0.06	0.06	-0.08	-0.06	-0.06	0.10	0.50	1.00	–	-0.03	0.07	0.13	-0.00	0.03	-0.01	-0.03	-0.01
Driving score	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pick/repl. speed	-0.07	0.10	-0.10	-0.17	0.17	0.01	-0.00	-0.01	0.00	-0.01	0.02	0.03	-0.04	-0.00	-0.03	0.03	0.11	-0.03	–	1.00	0.01	0.19	0.05	0.06	-0.01	-0.01	-0.00
Late shifts	-0.05	0.01	-0.01	-0.02	0.02	-0.01	0.03	-0.02	0.01	0.00	-0.00	0.00	-0.00	-0.03	-0.02	0.04	0.16	0.07	–	0.01	1.00	-0.03	-0.07	-0.10	-0.00	-0.02	-0.00
People/shift	-0.26	0.15	-0.15	-0.04	0.04	0.06	-0.02	-0.02	0.03	0.05	0.06	0.08	-0.12	-0.02	0.05	-0.04	0.65	0.13	–	0.19	-0.03	1.00	-0.12	-0.19	0.04	-0.02	-0.01
Captain abs. 4w	0.03	-0.00	0.00	0.10	-0.10	-0.02	0.00	0.01	0.02	-0.00	0.00	-0.02	0.01	-0.03	-0.08	0.09	-0.14	-0.00	–	0.05	-0.07	-0.12	1.00	0.64	0.11	0.03	0.04
Avg. captain abs.	0.01	0.01	-0.01	0.16	-0.16	-0.03	0.00	0.02	0.02	0.01	0.02	-0.01	-0.01	-0.03	-0.13	0.14	-0.22	0.03	–	0.06	-0.10	-0.19	0.64	1.00	-0.02	-0.02	0.01
Influenza	0.01	0.03	-0.03	0.00	-0.00	0.00	0.01	-0.01	0.04	0.04	-0.01	0.00	-0.01	0.00	0.00	-0.00	0.00	-0.01	–	-0.01	-0.00	0.04	0.11	-0.02	1.00	-0.33	-0.02
Econ. growth	0.01	0.00	-0.00	-0.01	0.01	0.00	0.00	-0.01	0.02	0.01	0.02	0.02	-0.03	0.01	-0.01	0.00	-0.04	-0.03	–	-0.01	-0.02	-0.02	0.03	-0.02	-0.33	1.00	0.08
Disruptions	-0.00	0.00	-0.00	0.00	-0.00	0.00	-0.00	0.00	0.01	-0.01	-0.02	0.00	0.01	-0.00	-0.00	0.00	-0.01	-0.01	–	-0.00	-0.00	-0.01	0.04	0.01	-0.02	0.08	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

Table 19: Correlation heatmap for NL Runner

	Abs. rate	Fixed-term	Permanent	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Late shifts	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	-0.05	0.05	-0.06	0.06	-0.10	0.05	0.08	-0.02	-0.02	-0.00	-0.02	0.03	-0.01	-0.00	0.01	-0.21	-0.18	0.03	-0.08	0.03	0.02	0.01	-0.01	-0.00
Fixed-term	-0.05	1.00	-1.00	0.02	-0.02	0.12	-0.09	-0.06	0.11	0.09	0.07	0.08	-0.16	-0.03	0.03	0.00	0.00	-0.08	0.01	0.01	-0.04	-0.06	0.02	-0.06	0.02
Permanent	0.05	-1.00	1.00	-0.02	0.02	-0.12	0.09	0.06	-0.11	-0.09	-0.07	-0.08	0.16	0.03	-0.03	-0.00	-0.00	0.08	-0.01	-0.01	0.04	0.06	-0.02	0.06	-0.02
Male	-0.06	0.02	-0.02	1.00	-1.00	-0.00	-0.01	0.02	0.02	0.01	0.00	-0.03	0.01	-0.02	0.03	-0.02	0.05	0.03	-0.08	0.07	-0.01	0.00	-0.00	-0.01	0.00
Female	0.06	-0.02	0.02	-1.00	1.00	0.00	0.01	-0.02	-0.02	-0.01	-0.00	0.03	-0.01	0.02	-0.03	0.02	-0.05	-0.03	0.08	-0.07	0.01	-0.00	0.00	0.01	-0.00
Age <26	-0.10	0.12	-0.12	-0.00	0.00	1.00	-0.75	-0.49	0.02	0.02	0.01	-0.04	0.01	0.02	0.01	-0.04	-0.16	-0.22	-0.16	-0.04	0.01	-0.00	0.02	-0.00	0.00
Age 26–40	0.05	-0.09	0.09	-0.01	0.01	-0.75	1.00	-0.21	-0.01	-0.02	-0.01	0.03	-0.01	-0.02	-0.00	0.04	0.11	0.13	0.07	0.06	-0.02	-0.04	-0.01	0.00	-0.00
Age 40+	0.08	-0.06	0.06	0.02	-0.02	-0.49	-0.21	1.00	-0.02	-0.01	-0.01	0.01	0.00	0.00	-0.01	0.01	0.09	0.16	0.14	-0.02	0.02	0.06	-0.01	0.00	-0.00
Tenure 0–93	-0.02	0.11	-0.11	0.02	-0.02	0.02	-0.01	-0.02	1.00	-0.02	-0.02	-0.04	-0.26	-0.01	0.01	-0.00	-0.01	-0.04	-0.01	-0.01	0.01	0.01	-0.02	-0.04	0.00
Tenure 94–187	-0.02	0.09	-0.09	0.01	-0.01	0.02	-0.02	-0.01	-0.02	1.00	-0.02	-0.05	-0.27	0.01	-0.00	-0.02	0.01	-0.01	-0.02	-0.01	0.01	0.01	-0.01	0.02	0.01
Tenure 188–365	-0.00	0.07	-0.07	0.00	-0.00	0.01	-0.01	-0.01	-0.02	-0.02	1.00	-0.07	-0.41	0.01	0.01	-0.03	0.02	0.00	-0.00	-0.01	0.02	0.00	0.02	0.01	-0.01
Tenure 366–730	-0.02	0.08	-0.08	-0.03	0.03	-0.04	0.03	0.01	-0.04	-0.05	-0.07	1.00	-0.77	-0.02	0.01	0.00	0.07	0.03	0.02	0.02	-0.02	-0.00	0.00	0.02	0.01
Tenure 731+	0.03	-0.16	0.16	0.01	-0.01	0.01	-0.01	0.00	-0.26	-0.27	-0.41	-0.77	1.00	0.01	-0.02	0.02	-0.06	-0.01	-0.01	-0.00	-0.00	-0.01	-0.00	-0.02	-0.00
Walking dist.	-0.01	-0.03	0.03	-0.02	0.02	0.02	-0.02	0.00	-0.01	0.01	0.01	-0.02	0.01	1.00	-0.78	-0.28	0.04	0.04	0.01	0.02	-0.02	-0.02	0.02	0.01	-0.00
Biking dist.	-0.00	0.03	-0.03	0.03	-0.03	0.01	-0.00	-0.01	0.01	-0.00	0.01	0.01	-0.02	-0.78	1.00	-0.38	-0.02	-0.03	-0.01	-0.01	0.02	-0.01	-0.01	-0.01	0.00
Driving dist.	0.01	0.00	-0.00	-0.02	0.02	-0.04	0.04	0.01	-0.00	-0.02	-0.03	0.00	0.02	-0.28	-0.38	1.00	-0.02	-0.02	-0.01	-0.01	0.01	0.04	-0.01	0.00	0.00
Shifts prev. week	-0.21	0.00	-0.00	0.05	-0.05	-0.16	0.11	0.09	-0.01	0.01	0.02	0.07	-0.06	0.04	-0.02	-0.02	1.00	0.76	0.09	0.36	-0.03	-0.02	-0.03	0.01	0.00
Paid hours prev. week	-0.18	-0.08	0.08	0.03	-0.03	-0.22	0.13	0.16	-0.04	-0.01	0.00	0.03	-0.01	0.04	-0.03	-0.02	0.76	1.00	0.10	0.25	-0.01	0.01	-0.04	0.02	-0.00
Driving score	0.03	0.01	-0.01	-0.08	0.08	-0.16	0.07	0.14	-0.01	-0.02	-0.00	0.02	-0.01	0.01	-0.01	-0.01	0.09	0.10	1.00	-0.04	-0.08	-0.12	0.02	-0.00	-0.00
Late shifts	-0.08	0.01	-0.01	0.07	-0.07	-0.04	0.06	-0.02	-0.01	-0.01	-0.01	0.02	-0.00	0.02	-0.01	-0.01	0.36	0.25	-0.04	1.00	-0.03	-0.01	-0.01	-0.00	0.01
Captain abs. 4w	0.03	-0.04	0.04	-0.01	0.01	0.01	-0.02	0.02	0.01	0.01	0.02	-0.02	-0.00	-0.02	0.02	0.01	-0.03	-0.01	-0.08	-0.03	1.00	0.59	-0.03	0.04	0.00
Avg. captain abs.	0.02	-0.06	0.06	0.00	-0.00	-0.00	-0.04	0.06	0.01	0.01	0.00	-0.00	-0.01	-0.02	-0.01	0.04	-0.02	0.01	-0.12	-0.01	0.59	1.00	0.00	0.00	0.00
Influenza	0.01	0.02	-0.02	-0.00	0.00	0.02	-0.01	-0.01	-0.02	-0.01	0.02	0.00	-0.00	0.02	-0.01	-0.01	-0.03	-0.04	0.02	-0.01	-0.03	0.00	1.00	-0.34	-0.04
Econ. growth	-0.01	-0.06	0.06	-0.01	0.01	-0.00	0.00	0.00	-0.04	0.02	0.01	0.02	-0.02	0.01	-0.01	0.00	0.01	0.02	-0.00	-0.00	0.04	0.00	-0.34	1.00	0.08
Disruptions	-0.00	0.02	-0.02	0.00	-0.00	0.00	-0.00	-0.00	0.00	0.01	-0.01	0.01	-0.00	-0.00	0.00	0.00	0.00	-0.00	-0.00	0.01	0.00	0.00	-0.04	0.08	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

Table 20: Correlation heatmap for FR Shopper

	Abs. rate	Fixed-term	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Pick/repl. speed	Late shifts	People/shift	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	–	-0.06	0.06	-0.05	0.03	0.03	-0.15	0.06	0.08	0.09	0.01	0.02	-0.02	0.01	-0.07	-0.45	–	-0.00	-0.11	-0.05	0.00	-0.07	-0.02	-0.07	0.01
Fixed-term	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Male	-0.06	–	1.00	-1.00	0.04	0.03	-0.10	0.06	0.03	0.00	-0.06	-0.13	0.04	0.03	-0.04	0.03	0.04	–	-0.03	0.11	0.04	0.03	0.04	-0.01	-0.01	-0.02
Female	0.06	–	-1.00	1.00	-0.04	-0.03	0.10	-0.06	-0.03	-0.00	0.06	0.13	-0.04	-0.03	0.04	-0.03	-0.04	–	0.03	-0.11	-0.04	-0.03	-0.04	0.01	0.01	0.02
Age <26	-0.05	–	0.04	-0.04	1.00	-0.75	-0.41	0.13	-0.00	-0.04	-0.08	-0.15	-0.07	-0.02	0.04	-0.06	-0.06	–	0.12	0.10	0.02	0.02	-0.01	-0.01	-0.01	-0.02
Age 26–40	0.03	–	0.03	-0.03	-0.75	1.00	-0.30	-0.05	0.04	0.03	-0.02	0.04	0.06	-0.03	0.01	0.04	0.04	–	-0.01	-0.05	0.01	-0.03	-0.06	0.01	-0.01	-0.00
Age 40+	0.03	–	-0.10	0.10	-0.41	-0.30	1.00	-0.13	-0.04	0.02	0.14	0.16	0.02	0.08	-0.08	0.04	0.02	–	-0.15	-0.08	-0.04	0.00	0.10	0.00	0.03	0.03
Tenure 0–93	-0.15	–	0.06	-0.06	0.13	-0.05	-0.13	1.00	-0.40	-0.41	-0.34	-0.18	0.02	0.03	-0.04	-0.02	0.05	–	0.15	0.27	0.19	0.06	0.13	0.04	0.00	-0.06
Tenure 94–187	0.06	–	0.03	-0.03	-0.00	0.04	-0.04	-0.40	1.00	-0.22	-0.18	-0.10	-0.02	0.01	-0.01	0.09	0.03	–	0.12	-0.06	0.06	0.02	0.02	-0.02	0.03	-0.01
Tenure 188–365	0.08	–	0.00	-0.00	-0.04	0.03	0.02	-0.41	-0.22	1.00	-0.19	-0.10	0.01	-0.01	0.01	0.05	0.02	–	-0.06	-0.09	-0.07	-0.05	-0.03	-0.06	0.03	0.08
Tenure 366–730	0.09	–	-0.06	0.06	-0.08	-0.02	0.14	-0.34	-0.18	-0.19	1.00	-0.08	-0.00	-0.03	0.03	0.03	0.03	–	-0.19	-0.11	-0.11	-0.01	-0.11	0.03	-0.06	0.00
Tenure 731+	0.01	–	-0.13	0.13	-0.15	0.04	0.16	-0.18	-0.10	-0.10	-0.08	1.00	-0.02	-0.04	0.04	0.04	0.05	–	-0.14	-0.08	-0.03	-0.05	-0.14	-0.01	-0.03	-0.00
Walking dist.	0.02	–	0.04	-0.04	-0.07	0.06	0.02	0.02	-0.02	0.01	-0.00	-0.02	1.00	-0.13	-0.20	-0.00	-0.01	–	-0.04	0.01	0.01	0.00	0.05	0.01	0.02	0.00
Biking dist.	-0.02	–	0.03	-0.03	-0.02	-0.03	0.08	0.03	0.01	-0.01	-0.03	-0.04	-0.13	1.00	-0.95	-0.01	-0.01	–	0.00	0.07	0.04	0.11	0.25	-0.01	-0.00	0.00
Driving dist.	0.01	–	-0.04	0.04	0.04	0.01	-0.08	-0.04	-0.01	0.01	0.03	0.04	-0.20	-0.95	1.00	0.01	0.01	–	0.01	-0.07	-0.04	-0.11	-0.26	0.01	-0.00	-0.00
Shifts prev. week	-0.07	–	0.03	-0.03	-0.06	0.04	0.04	-0.02	0.09	0.05	0.03	0.04	-0.00	-0.01	0.01	1.00	0.53	–	0.05	0.21	0.59	-0.00	-0.02	0.10	-0.07	0.02
Paid hours prev. week	-0.45	–	0.04	-0.04	-0.06	0.04	0.02	0.05	0.03	0.02	0.03	0.05	-0.01	-0.01	0.01	0.53	1.00	–	0.02	0.15	0.27	-0.04	-0.02	0.01	0.01	-0.01
Driving score	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pick/repl. speed	-0.00	–	-0.03	0.03	0.12	-0.01	-0.15	0.15	0.12	-0.06	-0.19	-0.14	-0.04	0.00	0.01	0.05	0.02	–	1.00	-0.06	0.15	-0.02	-0.14	0.03	-0.05	-0.01
Late shifts	-0.11	–	0.11	-0.11	0.10	-0.05	-0.08	0.27	-0.06	-0.09	-0.11	-0.08	0.01	0.07	-0.07	0.21	0.15	–	-0.06	1.00	0.23	0.15	0.28	-0.00	-0.02	0.01
People/shift	-0.05	–	0.04	-0.04	0.02	0.01	-0.04	0.19	0.06	-0.07	-0.11	-0.03	0.01	0.04	-0.04	0.59	0.27	–	0.15	0.23	1.00	0.13	0.14	-0.01	-0.17	-0.05
Captain abs. 4w	0.00	–	0.03	-0.03	0.02	-0.03	0.00	0.06	0.02	-0.05	-0.01	-0.05	0.00	0.11	-0.11	-0.00	-0.04	–	-0.02	0.15	0.13	1.00	0.44	0.02	-0.25	-0.08
Avg. captain abs.	-0.07	–	0.04	-0.04	-0.01	-0.06	0.10	0.13	0.02	-0.03	-0.11	-0.14	0.05	0.25	-0.26	-0.02	-0.02	–	-0.14	0.28	0.14	0.44	1.00	-0.01	-0.04	-0.02
Influenza	-0.02	–	-0.01	0.01	-0.01	0.01	0.00	0.04	-0.02	-0.06	0.03	-0.01	0.01	-0.01	0.01	0.10	0.01	–	0.03	-0.00	-0.01	0.02	-0.01	1.00	-0.27	-0.09
Econ. growth	-0.07	–	-0.01	0.01	-0.01	-0.01	0.03	0.00	0.03	0.03	-0.06	-0.03	0.02	-0.00	-0.00	-0.07	0.01	–	-0.05	-0.02	-0.17	-0.25	-0.04	-0.27	1.00	0.14
Disruptions	0.01	–	-0.02	0.02	-0.02	-0.00	0.03	-0.06	-0.01	0.08	0.00	-0.00	0.00	0.00	-0.00	0.02	-0.01	–	-0.01	0.01	-0.05	-0.08	-0.02	-0.09	0.14	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

Table 21: Correlation heatmap for FR Runner

	Abs. rate	Fixed-term	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Late shifts	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	–	-0.09	0.09	-0.05	0.04	0.01	-0.16	0.04	0.14	0.04	0.06	0.05	-0.05	0.01	-0.19	-0.24	0.01	-0.16	0.02	0.02	-0.01	-0.02	-0.00
Fixed-term	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Male	-0.09	–	1.00	-1.00	-0.08	0.05	0.08	0.04	0.02	-0.02	-0.04	-0.10	-0.03	0.06	-0.05	0.06	0.09	-0.06	0.07	-0.03	-0.10	0.01	-0.03	-0.01
Female	0.09	–	-1.00	1.00	0.08	-0.05	-0.08	-0.04	-0.02	0.02	0.04	0.10	0.03	-0.06	0.05	-0.06	-0.09	0.06	-0.07	0.03	0.10	-0.01	0.03	0.01
Age <26	-0.05	–	-0.08	0.08	1.00	-0.93	-0.26	0.07	0.00	-0.06	-0.05	-0.01	-0.09	0.07	0.01	-0.00	-0.05	-0.05	0.00	0.02	0.06	0.02	0.01	-0.02
Age 26–40	0.04	–	0.05	-0.05	-0.93	1.00	-0.12	-0.06	-0.01	0.05	0.05	0.02	0.09	-0.08	0.01	-0.01	0.04	0.03	-0.00	-0.03	-0.06	-0.02	-0.01	0.02
Age 40+	0.01	–	0.08	-0.08	-0.26	-0.12	1.00	-0.02	0.01	0.02	0.00	-0.02	0.02	0.02	-0.04	0.02	0.03	0.05	-0.00	0.02	-0.01	0.01	0.01	0.00
Tenure 0–93	-0.16	–	0.04	-0.04	0.07	-0.06	-0.02	1.00	-0.49	-0.45	-0.29	-0.12	-0.03	0.02	0.01	-0.08	0.01	0.02	0.05	0.00	-0.05	0.09	-0.06	0.01
Tenure 94–187	0.04	–	0.02	-0.02	0.00	-0.01	0.01	-0.49	1.00	-0.24	-0.15	-0.06	0.00	-0.00	-0.00	0.08	0.02	-0.02	0.05	0.01	0.00	0.02	0.00	-0.05
Tenure 188–365	0.14	–	-0.02	0.02	-0.06	0.05	0.02	-0.45	-0.24	1.00	-0.14	-0.06	0.02	-0.01	-0.01	0.06	0.01	-0.03	0.00	-0.01	0.01	-0.13	0.07	0.02
Tenure 366–730	0.04	–	-0.04	0.04	-0.05	0.05	0.00	-0.29	-0.15	-0.14	1.00	-0.04	0.02	-0.00	-0.01	0.10	0.13	0.03	-0.04	0.01	0.08	-0.01	0.00	-0.01
Tenure 731+	0.06	–	-0.10	0.10	-0.01	0.02	-0.02	-0.12	-0.06	-0.06	-0.04	1.00	0.01	-0.02	0.02	0.03	0.09	0.02	-0.02	-0.01	0.02	0.01	-0.00	0.02
Walking dist.	0.05	–	-0.03	0.03	-0.09	0.09	0.02	-0.03	0.00	0.02	0.02	0.01	1.00	-0.61	-0.27	0.02	-0.01	0.04	0.01	-0.00	-0.05	-0.01	-0.01	-0.00
Biking dist.	-0.05	–	0.06	-0.06	0.07	-0.08	0.02	0.02	-0.00	-0.01	-0.00	-0.02	-0.61	1.00	-0.60	0.01	0.05	-0.04	0.01	0.05	0.11	0.00	0.02	-0.01
Driving dist.	0.01	–	-0.05	0.05	0.01	0.01	-0.04	0.01	-0.00	-0.01	-0.01	0.02	-0.27	-0.60	1.00	-0.03	-0.05	0.01	-0.02	-0.05	-0.08	0.00	-0.01	0.01
Shifts prev. week	-0.19	–	0.06	-0.06	-0.00	-0.01	0.02	-0.08	0.08	0.06	0.10	0.03	0.02	0.01	-0.03	1.00	0.70	0.00	0.52	0.03	0.05	0.03	0.05	0.02
Paid hours prev. week	-0.24	–	0.09	-0.09	-0.05	0.04	0.03	0.01	0.02	0.01	0.13	0.09	-0.01	0.05	-0.05	0.70	1.00	-0.00	0.36	0.00	-0.03	0.01	0.08	0.04
Driving score	0.01	–	-0.06	0.06	-0.05	0.03	0.05	0.02	-0.02	-0.03	0.03	0.02	0.04	-0.04	0.01	0.00	-0.00	1.00	-0.06	0.01	0.01	0.08	-0.09	-0.01
Late shifts	-0.16	–	0.07	-0.07	0.00	-0.00	-0.00	0.05	0.05	0.00	-0.04	-0.02	0.01	0.01	-0.02	0.52	0.36	-0.06	1.00	-0.05	-0.09	0.01	0.01	-0.01
Captain abs. 4w	0.02	–	-0.03	0.03	0.02	-0.03	0.02	0.00	0.01	-0.01	0.01	-0.01	-0.00	0.05	-0.05	0.03	0.00	0.01	-0.05	1.00	0.40	0.07	-0.07	-0.04
Avg. captain abs.	0.02	–	-0.10	0.10	0.06	-0.06	-0.01	-0.05	0.00	0.01	0.08	0.02	-0.05	0.11	-0.08	0.05	-0.03	0.01	-0.09	0.40	1.00	0.01	0.04	0.01
Influenza	-0.01	–	0.01	-0.01	0.02	-0.02	0.01	0.09	0.02	-0.13	-0.01	0.01	-0.01	0.00	0.00	0.03	0.01	0.08	0.01	0.07	0.01	1.00	-0.46	-0.11
Econ. growth	-0.02	–	-0.03	0.03	0.01	-0.01	0.01	-0.06	0.00	0.07	0.00	-0.00	-0.01	0.02	-0.01	0.05	0.08	-0.09	0.01	-0.07	0.04	-0.46	1.00	0.20
Disruptions	-0.00	–	-0.01	0.01	-0.02	0.02	0.00	0.01	-0.05	0.02	-0.01	0.02	-0.00	-0.01	0.01	0.02	0.04	-0.01	-0.01	-0.04	0.01	-0.11	0.20	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

Table 22: Correlation heatmap for DE Shopper

	Abs. rate	Fixed-term	Permanent	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Pick/repl. speed	Late shifts	People/shift	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	0.04	-0.05	-0.01	0.01	0.07	-0.05	-0.03	0.06	-0.01	0.00	-0.04	-0.02	0.01	0.01	-0.02	0.04	-0.23	–	-0.01	0.03	0.06	0.04	0.08	0.01	0.03	0.01
Fixed-term	0.04	1.00	-0.99	0.05	-0.05	0.12	-0.01	-0.15	0.21	0.13	0.13	-0.11	-0.70	-0.07	0.01	0.04	-0.03	-0.13	–	0.06	0.09	-0.02	-0.16	-0.24	0.01	-0.01	-0.00
Permanent	-0.05	-0.99	1.00	-0.05	0.05	-0.13	0.01	0.15	-0.21	-0.13	-0.13	0.11	0.71	0.07	-0.02	-0.04	0.03	0.13	–	-0.06	-0.09	0.02	0.16	0.24	-0.01	0.01	0.00
Male	-0.01	0.05	-0.05	1.00	-1.00	0.03	0.05	-0.09	0.03	0.02	0.00	-0.03	-0.05	-0.01	0.01	-0.00	0.02	0.00	–	0.01	0.07	0.07	-0.03	-0.06	-0.00	-0.03	-0.02
Female	0.01	-0.05	0.05	-1.00	1.00	-0.03	-0.05	0.09	-0.03	-0.02	-0.00	0.03	0.05	0.01	-0.01	0.00	-0.02	-0.00	–	-0.01	-0.07	-0.07	0.03	0.06	0.00	0.03	0.02
Age <26	0.07	0.12	-0.13	0.03	-0.03	1.00	-0.71	-0.33	0.16	0.02	-0.04	-0.11	-0.12	0.01	0.03	-0.04	-0.07	-0.15	–	0.03	0.10	0.03	-0.00	0.02	0.02	0.03	0.02
Age 26–40	-0.05	-0.01	0.01	0.05	-0.05	-0.71	1.00	-0.44	-0.08	0.01	0.04	0.03	0.02	-0.04	-0.04	0.07	0.00	0.02	–	0.03	-0.03	-0.01	-0.04	-0.07	-0.02	-0.04	-0.02
Age 40+	-0.03	-0.15	0.15	-0.09	0.09	-0.33	-0.44	1.00	-0.10	-0.04	0.00	0.09	0.13	0.03	0.02	-0.05	0.09	0.17	–	-0.08	-0.09	-0.02	0.05	0.07	-0.01	0.02	0.01
Tenure 0–93	0.06	0.21	-0.21	0.03	-0.03	0.16	-0.08	-0.10	1.00	-0.35	-0.39	-0.33	-0.19	-0.03	-0.01	0.03	0.06	-0.05	–	0.06	0.17	0.09	-0.07	-0.11	0.10	0.04	0.04
Tenure 94–187	-0.01	0.13	-0.13	0.02	-0.02	0.02	0.01	-0.04	-0.35	1.00	-0.25	-0.21	-0.12	-0.01	-0.01	0.02	0.04	0.04	–	0.06	0.02	0.02	-0.07	-0.07	-0.06	0.00	-0.01
Tenure 188–365	0.00	0.13	-0.13	0.00	-0.00	-0.04	0.04	0.00	-0.39	-0.25	1.00	-0.23	-0.14	-0.01	-0.01	0.02	-0.05	0.01	–	-0.02	-0.07	-0.05	-0.01	-0.03	-0.06	-0.03	-0.01
Tenure 366–730	-0.04	-0.11	0.11	-0.03	0.03	-0.11	0.03	0.09	-0.33	-0.21	-0.23	1.00	-0.12	0.04	0.02	-0.05	-0.02	0.07	–	-0.07	-0.10	-0.02	0.09	0.13	-0.00	0.02	-0.02
Tenure 731+	-0.02	-0.70	0.71	-0.05	0.05	-0.12	0.02	0.13	-0.19	-0.12	-0.14	-0.12	1.00	0.04	0.01	-0.04	0.04	0.10	–	-0.06	-0.08	0.01	0.15	0.19	-0.02	-0.06	-0.01
Walking dist.	0.01	-0.07	0.07	-0.01	0.01	0.01	-0.04	0.03	-0.03	-0.01	-0.01	0.04	0.04	1.00	-0.39	-0.35	0.06	0.08	–	-0.01	-0.00	-0.01	0.04	0.10	-0.01	0.02	0.01
Biking dist.	0.01	0.01	-0.02	0.01	-0.01	0.03	-0.04	0.02	-0.01	-0.01	-0.01	0.02	0.01	-0.39	1.00	-0.73	-0.04	-0.05	–	0.02	-0.04	0.06	0.07	0.13	-0.01	0.02	0.01
Driving dist.	-0.02	0.04	-0.04	-0.00	0.00	-0.04	0.07	-0.05	0.03	0.02	0.02	-0.05	-0.04	-0.35	-0.73	1.00	-0.00	-0.01	–	-0.01	0.04	-0.05	-0.10	-0.20	0.01	-0.03	-0.01
Shifts prev. week	0.04	-0.03	0.03	0.02	-0.02	-0.07	0.00	0.09	0.06	0.04	-0.05	-0.02	0.04	0.06	-0.04	-0.00	1.00	0.48	–	0.06	0.26	0.48	-0.03	-0.04	0.04	-0.04	0.01
Paid hours prev. week	-0.23	-0.13	0.13	0.00	-0.00	-0.15	0.02	0.17	-0.05	0.04	0.01	0.07	0.10	0.08	-0.05	-0.01	0.48	1.00	–	-0.01	0.12	0.14	-0.06	-0.08	-0.05	-0.03	-0.01
Driving score	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Pick/repl. speed	-0.01	0.06	-0.06	0.01	-0.01	0.03	0.03	-0.08	0.06	0.06	-0.02	-0.07	-0.06	-0.01	0.02	-0.01	0.06	-0.01	–	1.00	0.05	0.22	0.01	0.01	-0.00	-0.08	-0.02
Late shifts	0.03	0.09	-0.09	0.07	-0.07	0.10	-0.03	-0.09	0.17	0.02	-0.07	-0.10	-0.08	-0.00	-0.04	0.04	0.26	0.12	–	0.05	1.00	0.20	-0.01	-0.02	0.04	0.03	0.01
People/shift	0.06	-0.02	0.02	0.07	-0.07	0.03	-0.01	-0.02	0.09	0.02	-0.05	-0.02	0.01	-0.01	0.06	-0.05	0.48	0.14	–	0.22	0.20	1.00	0.15	0.29	0.09	0.06	0.03
Captain abs. 4w	0.04	-0.16	0.16	-0.03	0.03	-0.00	-0.04	0.05	-0.07	-0.07	-0.01	0.09	0.15	0.04	0.07	-0.10	-0.03	-0.06	–	0.01	-0.01	0.15	1.00	0.58	0.14	0.09	0.04
Avg. captain abs.	0.08	-0.24	0.24	-0.06	0.06	0.02	-0.07	0.07	-0.11	-0.07	-0.03	0.13	0.19	0.10	0.13	-0.20	-0.04	-0.08	–	0.01	-0.02	0.29	0.58	1.00	0.01	0.18	0.06
Influenza	0.01	0.01	-0.01	-0.00	0.00	0.02	-0.02	-0.01	0.10	-0.06	-0.06	-0.00	-0.02	-0.01	-0.01	0.01	0.04	-0.05	–	-0.00	0.04	0.09	0.14	0.01	1.00	0.23	0.13
Econ. growth	0.03	-0.01	0.01	-0.03	0.03	0.03	-0.04	0.02	0.04	0.00	-0.03	0.02	-0.06	0.02	0.02	-0.03	-0.04	-0.03	–	-0.08	0.03	0.06	0.09	0.18	0.23	1.00	0.09
Disruptions	0.01	-0.00	0.00	-0.02	0.02	0.02	-0.02	0.01	0.04	-0.01	-0.01	-0.02	-0.01	0.01	0.01	-0.01	0.01	-0.01	–	-0.02	0.01	0.03	0.04	0.06	0.13	0.09	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

Table 23: Correlation heatmap for DE Runner

	Abs. rate	Fixed-term	Permanent	Male	Female	Age <26	Age 26–40	Age 40+	Tenure 0–93	Tenure 94–187	Tenure 188–365	Tenure 366–730	Tenure 731+	Walking dist.	Biking dist.	Driving dist.	Shifts prev. week	Paid hours prev. week	Driving score	Late shifts	Captain abs. 4w	Avg. captain abs.	Influenza	Econ. growth	Disruptions
Abs. rate	1.00	-0.00	-0.00	-0.03	0.03	-0.00	0.01	-0.01	-0.04	0.02	0.03	0.01	-0.01	-0.01	0.00	0.00	-0.13	-0.10	-0.01	-0.05	0.01	0.01	0.02	0.00	-0.01
Fixed-term	-0.00	1.00	-0.99	0.01	-0.01	0.08	-0.06	-0.04	0.12	0.07	0.06	0.01	-0.85	0.01	-0.00	-0.01	-0.02	-0.03	-0.01	-0.02	-0.00	0.01	0.01	0.08	0.02
Permanent	-0.00	-0.99	1.00	-0.01	0.01	-0.08	0.06	0.04	-0.12	-0.07	-0.07	-0.01	0.86	-0.01	0.00	0.01	0.02	0.03	0.01	0.02	0.00	-0.01	-0.01	-0.08	-0.02
Male	-0.03	0.01	-0.01	1.00	-1.00	-0.02	0.00	0.03	0.02	0.01	-0.01	-0.03	-0.01	-0.00	0.01	-0.01	0.04	0.03	-0.05	0.04	-0.01	-0.02	-0.01	-0.03	-0.03
Female	0.03	-0.01	0.01	-1.00	1.00	0.02	-0.00	-0.03	-0.02	-0.01	0.01	0.03	0.01	0.00	-0.01	0.01	-0.04	-0.03	0.05	-0.04	0.01	0.02	0.01	0.03	0.03
Age <26	-0.00	0.08	-0.08	-0.02	0.02	1.00	-0.83	-0.37	0.13	0.04	-0.04	-0.15	-0.08	0.03	0.01	-0.04	0.03	0.01	-0.07	0.07	0.01	0.01	0.00	0.00	-0.01
Age 26–40	0.01	-0.06	0.06	0.00	-0.00	-0.83	1.00	-0.21	-0.09	-0.02	0.03	0.10	0.06	-0.03	0.00	0.03	-0.01	-0.01	0.04	-0.04	-0.00	-0.00	-0.00	0.00	0.01
Age 40+	-0.01	-0.04	0.04	0.03	-0.03	-0.37	-0.21	1.00	-0.08	-0.03	0.02	0.10	0.05	-0.01	-0.02	0.03	-0.02	0.01	0.06	-0.06	-0.01	-0.02	-0.00	-0.01	-0.00
Tenure 0–93	-0.04	0.12	-0.12	0.02	-0.02	0.13	-0.09	-0.08	1.00	-0.41	-0.42	-0.33	-0.11	-0.02	0.01	0.01	-0.03	0.01	-0.02	-0.03	-0.01	0.02	0.00	0.03	0.06
Tenure 94–187	0.02	0.07	-0.07	0.01	-0.01	0.04	-0.02	-0.03	-0.41	1.00	-0.27	-0.22	-0.07	0.00	-0.00	-0.00	0.05	0.02	-0.02	0.02	0.00	-0.00	0.05	0.09	-0.01
Tenure 188–365	0.03	0.06	-0.07	-0.01	0.01	-0.04	0.03	0.02	-0.42	-0.27	1.00	-0.22	-0.08	0.02	-0.00	-0.01	0.00	0.00	0.01	0.02	0.01	-0.01	-0.04	0.04	-0.04
Tenure 366–730	0.01	0.01	-0.01	-0.03	0.03	-0.15	0.10	0.10	-0.33	-0.22	-0.22	1.00	-0.06	0.01	-0.01	-0.00	0.03	0.03	0.04	0.02	-0.00	-0.02	0.00	-0.13	-0.03
Tenure 731+	-0.01	-0.85	0.86	-0.01	0.01	-0.08	0.06	0.05	-0.11	-0.07	-0.08	-0.06	1.00	-0.01	-0.00	0.01	0.02	0.03	0.02	0.02	-0.00	-0.01	-0.01	-0.09	-0.02
Walking dist.	-0.01	0.01	-0.01	-0.00	0.00	0.03	-0.03	-0.01	-0.02	0.00	0.02	0.01	-0.01	1.00	-0.68	-0.27	-0.01	-0.02	0.01	0.01	0.01	0.03	-0.00	0.01	0.00
Biking dist.	0.00	-0.00	0.00	0.01	-0.01	0.01	0.00	-0.02	0.01	-0.00	-0.00	-0.01	-0.00	-0.68	1.00	-0.53	0.00	-0.00	-0.01	-0.01	-0.01	-0.02	0.00	0.01	-0.00
Driving dist.	0.00	-0.01	0.01	-0.01	0.01	-0.04	0.03	0.03	0.01	-0.00	-0.01	-0.00	0.01	-0.27	-0.53	1.00	0.02	0.02	-0.00	0.01	0.00	-0.00	-0.00	-0.02	0.00
Shifts prev. week	-0.13	-0.02	0.02	0.04	-0.04	0.03	-0.01	-0.02	-0.03	0.05	0.00	0.03	0.02	-0.01	0.00	0.02	1.00	0.69	-0.02	0.39	0.00	0.03	0.01	0.00	0.01
Paid hours prev. week	-0.10	-0.03	0.03	0.03	-0.03	0.01	-0.01	0.01	0.01	0.02	0.00	0.03	0.03	-0.02	-0.00	0.02	0.69	1.00	-0.03	0.27	0.01	0.02	-0.02	-0.03	-0.01
Driving score	-0.01	-0.01	0.01	-0.05	0.05	-0.07	0.04	0.06	-0.02	-0.02	0.01	0.04	0.02	0.01	-0.01	-0.00	-0.02	-0.03	1.00	-0.09	-0.00	-0.01	0.03	-0.05	-0.01
Late shifts	-0.05	-0.02	0.02	0.04	-0.04	0.07	-0.04	-0.06	-0.03	0.02	0.02	0.02	0.02	0.01	-0.01	0.01	0.39	0.27	-0.09	1.00	0.01	0.03	-0.01	-0.02	-0.01
Captain abs. 4w	0.01	-0.00	0.00	-0.01	0.01	0.01	-0.00	-0.01	-0.01	0.00	0.01	-0.00	-0.00	0.01	-0.01	0.00	0.00	0.01	-0.00	0.01	1.00	0.35	0.09	0.05	-0.02
Avg. captain abs.	0.01	0.01	-0.01	-0.02	0.02	0.01	-0.00	-0.02	0.02	-0.00	-0.01	-0.02	-0.01	0.03	-0.02	-0.00	0.03	0.02	-0.01	0.03	0.35	1.00	0.01	0.03	0.00
Influenza	0.02	0.01	-0.01	-0.01	0.01	0.00	-0.00	-0.00	0.00	0.05	-0.04	0.00	-0.01	-0.00	0.00	-0.00	0.01	-0.02	0.03	-0.01	0.09	0.01	1.00	0.20	0.12
Econ. growth	0.00	0.08	-0.08	-0.03	0.03	0.00	0.00	-0.01	0.03	0.09	0.04	-0.13	-0.09	0.01	0.01	-0.02	0.00	-0.03	-0.05	-0.02	0.05	0.03	0.20	1.00	0.08
Disruptions	-0.01	0.02	-0.02	-0.03	0.03	-0.01	0.01	-0.00	0.06	-0.01	-0.04	-0.03	-0.02	0.00	-0.00	0.00	0.01	-0.01	-0.01	-0.01	-0.02	0.00	0.12	0.08	1.00

Note: Blue cells indicate positive correlations and red cells indicate negative correlations. Darker cells indicate stronger absolute correlations. "–" indicates undefined correlations due to missing values or insufficient variation.

H VIF Tables

Table 24: Shopper absence-rate OLS VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Permanent contract	3.99		2.42
Female	1.89	1.83	1.37
Age 26–40	3.64	1.70	2.38
Age 40+	3.60	1.41	1.62
Tenure 94–187 days	1.22	1.50	1.51
Tenure 188–365 days	1.96	1.64	1.65
Tenure 366–730 days	6.37 (M)	1.62	1.68
Tenure 731–1095 days	6.77 (M)	1.22	1.88
Tenure 1096–1460 days	3.98	1.06	1.32
Tenure 1461+ days	5.60 (M)	1.00	1.38
Distance			
Biking distance	5.07 (M)	5.42 (M)	2.94
Driving distance	5.74 (M)	7.92 (M)	2.67
Scheduling: total volume			
Total shifts in previous 4 weeks	23.17 (H)	83.14 (H)	34.88 (H)
Scheduling: weekday composition			
Monday shifts	5.05 (M)	16.74 (H)	8.64 (M)
Friday shifts	4.96	24.59 (H)	9.64 (M)
Weekend shifts	3.79	8.00 (M)	4.50
Scheduling: shift time			
Morning shifts	3.28	10.30 (H)	4.72
Evening/night shifts	1.10	1.00	1.17
Scheduling: shift type			
Chilled shifts	3.57	4.38	2.87
Frozen shifts	1.33	1.51	1.26
Operational and performance context			
People per shift	5.79 (M)	6.46 (M)	5.73 (M)
Picking/replenishment speed	1.67	3.12	2.05
Late shifts	1.15	1.67	1.54
Leadership/team context			
Captain absence rate	3.91	3.39	4.54
Exogenous controls			
Influenza level	1.30	1.19	1.15
Economic growth	2.44	2.11	1.62
Major operational disruptions	1.07	1.13	1.06
VIF model information			
Covariates in VIF model	27	26	27

Notes: Values are variance inflation factors. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

Table 25: Runner absence-rate OLS VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Permanent contract	4.06		3.99
Female	1.26	1.36	1.14
Age 26–40	1.48	1.38	1.63
Age 40+	1.25	1.06	1.20
Tenure 94–187 days	1.11	1.41	1.56
Tenure 188–365 days	1.26	1.41	1.60
Tenure 366–730 days	1.95	1.22	1.50
Tenure 731–1095 days	4.32	1.04	3.67
Tenure 1096–1460 days	3.14	1.02	1.30
Tenure 1461+ days	2.71	1.00	1.07
Distance			
Biking distance	2.36	2.44	3.21
Driving distance	1.33	1.50	1.67
Scheduling: total volume			
Total shifts in previous 4 weeks	46.77 (H)	70.65 (H)	26.54 (H)
Scheduling: weekday composition			
Monday shifts	4.78	6.34 (M)	3.46
Friday shifts	3.88	6.83 (M)	4.03
Weekend shifts	2.56	3.07	2.74
Scheduling: shift time			
Morning shifts	13.31 (H)	2.41	3.73
Evening/night shifts	19.93 (H)	37.86 (H)	10.99 (H)
Operational and performance context			
Driving score			8.94 (M)
Late shifts	1.54	2.56	1.49
Leadership/team context			
Captain absence rate	1.36	1.22	1.63
Exogenous controls			
Influenza level	1.30	1.36	1.10
Economic growth	2.39	2.14	1.56
Major operational disruptions	1.07	1.13	1.04
VIF model information			
Covariates in VIF model	23	22	24

Notes: Values are variance inflation factors. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

Table 26: Shopper robustness OLS VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Female	2.00	1.66	1.38
Age 26–40	2.97	1.57	2.04
Age 40+	2.53	1.24	1.40
Tenure 94–187 days	1.52	1.26	1.43
Tenure 188–365 days	2.49	1.24	1.34
Tenure 366–730 days	10.28 (H)	1.17	1.25

Variable	NL	FR	DE
Tenure 731–1095 days	8.15 (M)	1.05	1.07
Tenure 1096–1460 days	2.08	1.01	1.01
Tenure 1461+ days	3.40		1.03
Distance			
Biking distance	4.84	5.58 (M)	3.53
Driving distance	5.25 (M)	11.08 (H)	3.29
Scheduling: total volume			
Total shifts in observation period	22.64 (H)	60.89 (H)	41.60 (H)
Scheduling: weekday composition			
Friday shifts	6.19 (M)	21.32 (H)	16.64 (H)
Weekend shifts	3.64	7.87 (M)	7.33 (M)
Scheduling: shift time			
Morning shifts	3.28	15.62 (H)	7.05 (M)
Evening/night shifts	1.22		1.28
Scheduling: shift type			
Chilled shifts	4.31	5.32 (M)	3.42
Frozen shifts	1.48	1.59	1.30
Operational and performance context			
People per shift	10.33 (H)	12.28 (H)	14.50 (H)
Picking/replenishment speed	1.88	4.95	3.52
Late shifts	1.26	2.37	1.91
Leadership/team context			
Captain absence rate	11.32 (H)	11.74 (H)	17.83 (H)
Exogenous controls			
Influenza level	1.57	1.21	1.35
Economic growth	10.77 (H)	2.18	2.29
Major operational disruptions	2.42	1.27	1.19
VIF model information			
Covariates in VIF model	25	23	25

Notes: Values are variance inflation factors from the person-level robustness OLS models. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

Table 27: Runner robustness OLS VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Female	1.27	1.40	1.17
Age 26–40	1.40	1.42	1.47
Age 40+	1.21	1.07	1.13
Tenure 94–187 days	2.31	1.22	1.33
Tenure 188–365 days	3.30	1.16	1.23
Tenure 366–730 days	7.30 (M)	1.06	1.10
Tenure 731–1095 days	33.39 (H)	1.01	1.01
Tenure 1096–1460 days	7.04 (M)	1.01	1.00
Tenure 1461+ days	6.12 (M)		1.00
Distance			
Biking distance	2.31	3.93	3.37
Driving distance	1.33	2.04	1.76

Variable	NL	FR	DE
Scheduling: total volume			
Total shifts in observation period	47.98 (H)	58.42 (H)	27.36 (H)
Scheduling: weekday composition			
Friday shifts	4.10	6.25 (M)	4.89
Weekend shifts	2.33	3.30	3.23
Scheduling: shift time			
Morning shifts	14.81 (H)	2.26	3.71
Evening/night shifts	23.14 (H)	37.58 (H)	14.26 (H)
Operational and performance context			
People per shift	66.38 (H)	13.74 (H)	3.08
Picking/replenishment speed	4.08		2.71
Driving score			16.33 (H)
Late shifts	1.96	3.47	1.81
Leadership/team context			
Captain absence rate	1.87	2.29	5.19 (M)
Exogenous controls			
Influenza level	1.55	1.41	1.29
Economic growth	9.12 (M)	2.44	2.07
Major operational disruptions	1.99	1.37	1.24
VIF model information			
Covariates in VIF model	23	21	24

Notes: Values are variance inflation factors from the person-level robustness OLS models. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

Table 28: Shopper survival model VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Permanent contract	2.43		1.64
Female	1.09	1.14	1.03
Age 26–40	1.70	1.10	1.18
Age 40+	1.69	1.18	1.21
Tenure 0–93 days	1.03	3.19	2.96
Tenure 94–187 days	1.05	2.63	2.25
Tenure 188–365 days	1.12	2.34	2.22
Tenure 731–1095 days	1.40	1.17	1.30
Tenure 1096–1460 days	1.41	1.04	1.10
Tenure 1461+ days	2.78		1.42
Distance			
Walking distance	1.13	1.09	1.15
Driving distance	1.18	1.13	1.16
Scheduling: total volume			
Total shifts in previous 4 weeks	1.75	1.99	1.98
Scheduling: weekday composition			
Friday shifts	1.33	1.52	1.39
Weekend shifts	1.16	1.12	1.10
Scheduling: shift time			
Morning shifts	1.41	1.42	1.47

Variable	NL	FR	DE
Evening/night shifts	1.11		1.16
Scheduling: shift type			
Chilled shifts	1.23	1.22	1.18
Frozen shifts	1.15	1.26	1.12
Operational and performance context			
People per shift	1.18	1.32	1.21
Picking/replenishment speed	1.06	1.15	1.11
Late shifts	1.07	1.16	1.10
Leadership/team context			
Captain absence rate	1.07		1.12
Exogenous controls			
Influenza level	1.15	1.24	1.11
Economic growth	1.15	1.28	1.08
Major operational disruptions	1.01	1.04	1.04
VIF model information			
Observations used for VIF	5459	4053	38536
Covariates in VIF model	26	22	26

Notes: Values are variance inflation factors. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

Table 29: Runner survival model VIF diagnostics

Variable	NL	FR	DE
Employee profile			
Permanent contract	1.32		1.06
Female	1.05	1.09	1.02
Age 26–40	1.19	1.09	1.07
Age 40+	1.13	1.05	1.06
Tenure 0–93 days	1.13	3.65	2.62
Tenure 94–187 days	1.13	3.11	2.31
Tenure 188–365 days	1.33	2.96	2.21
Tenure 731–1095 days	2.54	1.17	1.09
Tenure 1096–1460 days	2.15	1.07	1.01
Tenure 1461+ days	2.16	1.02	1.05
Distance			
Walking distance	1.11	1.15	1.08
Driving distance	1.12	1.15	1.08
Scheduling: total volume			
Total shifts in previous 4 weeks	12.21 (H)	16.62 (H)	5.57 (M)
Scheduling: weekday composition			
Friday shifts	1.96	2.40	1.64
Weekend shifts	1.16	1.34	1.21
Scheduling: shift time			
Morning shifts	8.51 (M)	1.95	2.70
Evening/night shifts	9.49 (M)	13.27 (H)	3.85
Operational and performance context			
People per shift	1.33	1.51	1.05
Driving score	1.11	1.06	1.04
Late shifts	1.18	1.30	1.15

Variable	NL	FR	DE
Leadership/team context			
Captain absence rate	1.03		1.01
Exogenous controls			
Influenza level	1.30	1.39	1.12
Economic growth	1.31	1.29	1.11
Major operational disruptions	1.03	1.03	1.02
VIF model information			
Observations used for VIF	1853	1602	35760
Covariates in VIF model	24	22	24

Notes: Values are variance inflation factors. M = moderate VIF flag; H = high VIF flag. Blank cells indicate that the variable was not included in that country-specific model.

I Confidential Annex

I.1 Operationalization

Table 30: Overview of conceptual and operational variables

Variable group	Conceptual variable	Operational variable(s)
Employee	Age	Age category
Employee	Gender	Gender dummy variable
Employee	Tenure	Tenure category
Employee	Contract type	Contract-type dummy variables
Employee	Distance to work	Commuting-distance category
Operational	Recent scheduling volume	Number of shifts per week
Operational	Shift day	Number of shifts per weekday
Operational	Shift time	Number of shifts per shift-time category
Operational	Shift type	Number of shifts per shift-type category; included only for Shoppers
Operational	Role-specific performance	Driver score for Runners; Picking/Replenishment speed for Shoppers
Operational	Lateness	Number of late shifts
Operational	Leadership absence	Captain or Lead absence rate
Operational	Staffing context	Number of people per shift
Exogenous factors	Influenza level	Influenza level
Exogenous factors	Tightness labour market	Economic growth
Exogenous factors	Major operational disruptions	Major operational disruptions dummy variable

The included variables follow directly from the conceptualization, with operational adjustments to fit the operations of the logistics sector and Picnic's case. Employee characteristics are defined similar to previous literature discussed in the review in chapter 2. Age and Tenure have been categorised to better account for non-linear mechanisms. The bin-sizes were established to create an even spread for each country. Distance-to-work had not yet been researched properly yet in terms of sickness absence. This variable is binned to match different types of commuting options (excluding public transport), to also function as a proxy for mobility. Walking-distance: 0-2 km, Biking-distance: 3-10 km, Driving-distance: 10+km. Nevertheless, this proxy is limited, and will be interpreted as such.

Operational characteristics are logically more dependent on the logistics sector and Picnic's operations, and have therefore been defined appropriately. Scheduling variables from Nicholson's (1998) research have been included in similar style through shift-time and day-of-the-week. Shift-type is more context dependent, typing in what temperature zone shoppers have worked during a shift, and will be categorized in the 3 options: Frozen/Chilled/Ambient. Performance variables are role-dependent as the review stated, and have been included as the main performance indicator of each role. Lateness, Leadership absence and staffing context have been implemented similairly to previous research, but now as a time-dependent variable.

Exogenous factors have been included similair to the conceptualization. However, because no data on the tightness of the labourmarket was available with the same granularity. Economic growth was selected instead, this serves as a good direct proxy to the tightness of the labour market. A high economic growth generally corresponds to higher labour demand causing a tight market (OECD, 2020). The quarterly economic-growth data were linearly interpolated to weekly values so that the indicator could be aligned with the employee-week structure of the analysis and reflect gradual changes between quarters. A similar interpolation procedure was applied to the influenza data. Because national reporting systems differ across countries, the resulting indicators were standardised before the regression analysis to improve comparability in the intensity of seasonal influenza outbreaks across markets. Major operational disruptions were included as a binary variable, coded as 1 when a disruption occurred during a given week. This specification does not distinguish between disruptions lasting a single day and those affecting operations throughout the entire week, nor does it capture differences in severity or operational impact.

Absence-rate OLS (Person-week level) For the main absence-rate analysis, as well as for the exploratory determinants analysis, the dataset is structured at the person-week level. Each observation represents one employee in one calendar week. This structure allows weekly absence intensity to be related to employee characteristics, job and operational context, and external contextual variables. The dependent variable is the weekly absence rate, calculated as the share of expected working time that was lost due to sickness absence within a given employee-week. Expected working time is based on the employee's contracted hours or working pattern over the preceding 13 weeks. For more details, see 3.1.3.

Because the same employee can appear in multiple weeks, this dataset contains repeated observations per individual. This structure is useful because it preserves week-level variation, but it also means that observations within employees may be correlated. For this reason, the person-week OLS is complemented by a person-level robustness analysis.

The employee characteristics and exogenous factors are operationalised using the last available value within each week. This ensures that these variables reflect the employee's status and external conditions as accurately as possible during the week of observation.

Worker-profile characteristics are operationalised using the average value over the preceding four weeks. This lagged four-week window is used to capture recent work patterns and operational conditions, rather than only the circumstances of the current week. This is important because sickness absence may be related to accumulated exposure to specific scheduling patterns, workload, lateness, or local operational conditions. This matches the idea of Allegro & Veerman (1998), that sickness absence can be triggered by a build up of health complaints, fatigue, strain or private circumstances. The four-week window is a methodological choice rather than a theoretically fixed exposure period. It was selected because it corresponds to approximately one month of recent work history and therefore balances two requirements. A shorter window would be more sensitive to incidental weekly scheduling variation, while a longer window could dilute the influence of recent operational conditions and mix current work exposure with less relevant past circumstances. The four-week average therefore provides a stable but still recent measure of work-context exposure, while ensuring that explanatory variables are measured before the observed sickness absence outcome.

The scheduling variables, including day of the week, shift type and shift time, are measured as average counts per week over this four-week period. They are not expressed as shares of total scheduled shifts for two reasons. First, counts are easier to interpret in the regression models. Second, employees who have been absent for a longer period may have no planning data in a given week, making share-based measures undefined or misleading. Using average counts therefore preserves comparability across observations and avoids dropping weeks without scheduled shifts. Including the number of shifts per week ensures that the model controls for the overall amount of scheduled work and distinguishes weeks without planning data from weeks in which an employee was scheduled for specific shift patterns.

The coefficients for these scheduling variables should be interpreted as associations between recent scheduling patterns and sickness absence. For example, a coefficient for Monday shifts does not mean that sickness absence is literally lower or higher on Mondays. Instead, it indicates how the weekly absence rate changes, on average, for employees who were more frequently scheduled on Mondays in the preceding four weeks, holding the other model variables constant. Detailed operationalization of the variables included in the analysis are provided in Appendix A.

Absence-rate robustness OLS (Person-level) To assess whether the main absence-rate findings are robust to the repeated person-week structure, an additional person-level aggregated dataset is constructed. In this dataset, each employee appears only once. Sickness absence hours and expected working hours are aggregated over the full observation period, after which the person-level absence rate is calculated as total sickness absence hours divided by total expected working hours.

This dataset is used for a robustness OLS model. The purpose of this model is not to replace the person-week analysis, but to validate whether the main associations remain similar when the data are collapsed to one observation per employee. This removes within-person repetition and therefore reduces concerns that the main OLS results are driven by correlation between repeated weekly observations from the same employee.

All independent variables are included as an average of the observed total weeks per employee. Detailed operationalization of the variables included in the survival analysis are provided in Appendix A.

Absence-spell Survival analysis (Person-spell level) For the survival analysis, the dataset is structured at the absence-spell level. Each observation represents one sickness absence spell. The dependent variable is the duration of the sickness absence spell. For further explanation of the operationalization of absence duration, see Section 3.2. Because this dataset includes only absence spells, the population of the dataset differs from the OLS datasets. This dataset only includes Picnic employees who were sick once during 2024 and 2025, where OLS includes the entire workforce during that timespan.

Employee-characteristics and exogenous factors are operationalized as the employee state at the start of each spell. Worker-profile characteristics are operationalised using the average value over the four weeks preceding the absence-spell. A a similair assumption to the absence-rate OLS is made for this operationalization. Scheduling variable are again defined as counts. Detailed operationalization of the variables included in the survival analysis are provided in Appendix A.

I.2 Data Sources & NaN Values

The empirical analysis combines several internal Picnic data sources with external contextual indicators. The internal datasets are used to construct three analytical datasets: an employee-week dataset for the main absence-rate OLS models, a person-level aggregated dataset for the robustness OLS models, and an absence-spell dataset for the survival analysis of sickness spell duration. This structure allows sickness absence to be analysed both as an overall absence burden and as a duration process. The dataset combines several internal Picnic data sources with external contextual indicators.

Workday is used as the authoritative source for employee and contract information, as well as for data at the absence-spell level. It provides the start and end dates of sickness absence spells and contains personnel metadata such as employment contract type, role, site or facility assignment, age, and gender. These variables are essential for linking sickness absence outcomes to employee characteristics and contractual conditions.

Kronos is the primary source for shift-level operational data. It contains detailed information on planned shifts, shift timing, shift duration, lateness, role, and other operational shift characteristics. These data are used to construct variables that describe the working conditions faced by employees in a given week.

However, raw Kronos data also contain operational inconsistencies. For example, some shifts may not have been clocked correctly, employees may forget to clock out, or changes may occur during operations without being fully reflected in the schedule. Therefore, Kronos data are cleaned before being used in the analysis. For worked hours and sickness absence hours, Timesheets are used instead of raw Kronos records. Timesheets provide the corrected administrative record of paid worked hours and paid sickness absence hours. This makes them more suitable for constructing the weekly absence-rate outcome used in the OLS models.

Timesheet data are used to construct the weekly absence outcome in the person-week analysis. These records are consistent with Workday absence records but provide the information at the weekly-hours level. This is essential for the OLS analysis, where the dependent variable is measured as the share of expected working time lost to sickness absence in a given week. Workday data, by contrast, are used for the spell-level survival analysis, where the relevant unit of observation is the sickness absence spell rather than the employee-week.

The timesheet data only cover employees with Picnic contracts and do not include employees hired through temporary employment agencies (TAs). This limitation is not expected to strongly affect the main analysis, as the largest share of employees in the Netherlands and Germany, and all employees in France, are employed directly through Picnic contracts. The analysis therefore focuses on Picnic employees rather than TA workers. This focus also improves data quality, since Picnic-contracted employees are more consistently registered across systems such as Kronos and Workday. For TA workers, data extraction is more prone to administrative inconsistencies and missing values because relevant information is partly managed by external agencies rather than directly within Picnic's internal systems. As a result, excluding TA workers reduces missingness and improves consistency across the linked datasets.

External sources were used to account for external shocks that may influence absence behaviour independently of Picnic's internal operations, the dataset is augmented with country-level and time-varying contextual indicators.

Weekly influenza-level data were obtained from the relevant national public-health institutes: the National Institute for Public Health and the Environment in the Netherlands, the Robert Koch Institute in Germany, and Santé publique France in France (RIVM, 2025; Robert Koch Institute, 2025; Santé publique France, 2025).

Second, quarterly real GDP growth was included to control for changes in the broader macroeconomic environment. Country-level data were obtained from the OECD Quarterly National Accounts (2026). Economic growth was used as an indirect proxy for labour-market conditions, which may influence sickness absence through employment security, outside employment opportunities, and workload pressure. Because GDP growth does not directly measure labour-market tightness, the underlying mechanism cannot be identified from this indicator alone.

Third, major operational disruptions were included to capture exceptional events that could temporarily affect Picnic's operational workforce, such as severe weather, road blockades, protests, urban access restrictions, and transport or security disruptions. Relevant events were identified through informal interviews with People Partners, operational analysts, and Fulfilment Centre and Hub leads, and were included when stakeholders reported substantial effects on staffing, accessibility, deliveries, or fulfilment-centre operations. The resulting events were translated into country- and week-specific indicators. Because event selection relied partly on stakeholder judgement, some subjectivity and cross-country variation are unavoidable. Stronger associations in one country may therefore reflect the identification of more relevant events rather than a genuinely larger disruption effect. National public holidays, without transport disruption, were excluded because they are anticipated and form part of regular operational planning; previous research also found no elevated sickness absence on bridging days around public holidays (Leoni & Böheim, 2018). Appendix I provides an overview of the included events.

Sources of NaN's

The planning data and timesheet worked-hours data were combined to construct an employee-week dataset. The purpose of this merge was to link each employee's realised labour exposure, measured through worked hours in the timesheet data, to the planned operational context in which this work took place. For the main employee-week OLS dataset, time-varying operational variables were constructed over the four weeks preceding the focal employee-week. This means that sickness absence in week t is explained using the employee's observed work context in the previous four weeks rather than information from the same week. This lagged structure preserves temporal ordering and reduces the risk that sickness absence in the focal week affects the explanatory variables. However, it also means that missing values can arise when an employee has no observed or matchable work history in the preceding four-week window.

The largest source of missingness is therefore found in the previous-four-week planning-derived variables. These include the number of shifts, weekday shift counts, shift-time counts, shift-type counts for Shoppers, late shifts, and people per shift. In the main OLS dataset, these variables show repeated missingness within each country-role group because they are derived from the same underlying planning-history merge. Missingness in these variables does not necessarily mean that the employee did not belong to the workforce or that their employee record was incomplete. Instead, it indicates that no usable planning history was available for that employee in the relevant preceding four-week window.

In addition to planning-related missing values, some variables were incomplete in the original administrative data. This applies especially to employee background variables such as gender, address and postal code information. Missingness in these variables may arise from differences in administrative registration, incomplete employee records or privacy restrictions.

NaN-handling

Before estimating the regression and survival models, missing values were systematically assessed for each dataset. Separate missing-value overviews were produced for the Shopper and Runner datasets, reporting the number of missing values, percentage missing, number of non-missing observations, and number of unique non-missing values for each variable. An overview of the missing values before NaN-handling per dataset can be found in appendix I.

The core metrics used to construct the dependent variables did not contain missing values in the final analytical datasets. For the weekly and aggregated OLS datasets, the base variables were worked hours and sickness absence hours. For the survival dataset, the base variables were the absence-spell start and end dates.

For operational exposure variables based on recent work history, missing values were interpreted as indicating that the employee had no observed shifts in the relevant preceding period. Lagged shift-history variables, including weekday, department and time-of-day shift counts, performance, people per shift, late-shift share, captain absence and worked hours, were therefore coded as zero when missing.

This approach was considered preferable to median imputation or complete-case deletion. Median imputation would assign an artificial operational context, such as an average performance level or team size, to employees who had not worked any shifts during the relevant period. Complete-case deletion would remove these employees and could introduce selection bias, because exclusion would be directly related to recent labour exposure. Zero-coding instead preserves the analytical sample and consistently represents the absence of operational exposure. Since these variables do not otherwise take genuine zero values, zero uniquely identifies observations without recent shift history.

A limitation remains that variables such as performance, people per shift and captain absence are conceptually undefined when no shifts were observed, rather than substantively equal to zero. The inclusion of the total number of shifts in the preceding period partly addresses this issue, as observations without recent shifts are separately identified by a shift count of zero.

For the limited missing demographic variables, NaN-values were handled through median imputation. Missing age, tenure, and distance-to-location values were filled using the median within the most relevant available group, usually country-location first, followed by country-level and global medians. After imputing distance to location, commuting-distance categories were derived.

I.3 NaN Tables

Nan-values Overview - OLS dataset

Table 31: Missing values by country and role for the main OLS dataset before NaN handling

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Dataset size						
Number of observations	72,120	53,255	219,072	413,441	32,761	28,517
Employee profile						
Contract category	26 (0.0%)	1 (0.0%)	231 (0.1%)	257 (0.1%)	63 (0.2%)	68 (0.2%)
Gender	0 (0.0%)	71 (0.1%)	2,336 (1.1%)	6,286 (1.5%)	35 (0.1%)	73 (0.3%)
Age	0 (0.0%)	0 (0.0%)	3 (0.0%)	25 (0.0%)	4 (0.0%)	9 (0.0%)
Tenure days	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Postal code	0 (0.0%)	0 (0.0%)	507 (0.2%)	41 (0.0%)	218 (0.7%)	448 (1.6%)
Distance to work						
Distance to location	0 (0.0%)	104 (0.2%)	507 (0.2%)	515 (0.1%)	218 (0.7%)	448 (1.6%)
Scheduling: total volume, previous 4 weeks						
Total shifts in previous 4 weeks	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Paid hours in previous 4 weeks	775 (1.1%)	884 (1.7%)	8,142 (3.7%)	16,377 (4.0%)	2,271 (6.9%)	1,757 (6.2%)
Scheduling: weekday composition, previous 4 weeks						
Monday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Tuesday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Wednesday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Thursday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Friday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Saturday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Sunday shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Scheduling: shift time, previous 4 weeks						
Morning shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Afternoon shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Evening shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)

Continued on next page

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Night shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Scheduling: shift type, previous 4 weeks						
Ambient shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Chilled shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Frozen shifts	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Operational/performance						
Picking/replenishing speed	18,546 (25.7%)		33,491 (15.3%)		6,560 (20.0%)	
People per shift	17,767 (24.6%)		30,918 (14.1%)		5,247 (16.0%)	
Driving score		6,278 (11.8%)		90,039 (21.8%)		5,313 (18.6%)
Late shifts	17,767 (24.6%)	6,275 (11.8%)	30,918 (14.1%)	88,650 (21.4%)	5,247 (16.0%)	5,305 (18.6%)
Leadership/team context						
Captain absence rate previous 4 weeks	157 (0.2%)	60 (0.1%)	17 (0.0%)	6,325 (1.5%)	0 (0.0%)	296 (1.0%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. All scheduling variables refer to the previous four weeks. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset.

NaN-values overview - Robustness OLS dataset

Table 32: Missing values by country and role for the robustness OLS dataset before NaN handling

Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Dataset size						
Number of observations	1,479	1,388	9,187	18,046	2,373	1,789
Employee profile						
Contract category	0 (0.0%)	1 (0.1%)	9 (0.1%)	7 (0.0%)	6 (0.3%)	8 (0.4%)
Gender	0 (0.0%)	3 (0.2%)	76 (0.8%)	186 (1.0%)	5 (0.2%)	8 (0.4%)
Age	0 (0.0%)	0 (0.0%)	0 (0.0%)	16 (0.1%)	1 (0.0%)	2 (0.1%)
Tenure days	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Postal code	0 (0.0%)	0 (0.0%)	55 (0.6%)	2 (0.0%)	8 (0.3%)	32 (1.8%)
Distance to work						

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Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Distance to location	0 (0.0%)	6 (0.4%)	55 (0.6%)	11 (0.1%)	8 (0.3%)	32 (1.8%)
Scheduling: weekday composition, total-period averages						
Monday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Tuesday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Wednesday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Thursday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Friday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Saturday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Sunday shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Scheduling: shift time, total-period averages						
Morning shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Afternoon shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Evening shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Night shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Scheduling: shift type, total-period averages						
Ambient shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Chilled shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Frozen shifts	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Operational/performance						
Average picking/replenishing speed	149 (10.1%)		90 (1.0%)		49 (2.1%)	
Average people per shift	146 (9.9%)		71 (0.8%)		49 (2.1%)	
Average driving score		55 (4.0%)		1,539 (8.5%)		139 (7.8%)
Average late shifts	146 (9.9%)	55 (4.0%)	71 (0.8%)	1,395 (7.7%)	49 (2.1%)	138 (7.7%)
Leadership/team context						
Average captain absence rate	0 (0.0%)	0 (0.0%)	0 (0.0%)	264 (1.5%)	0 (0.0%)	24 (1.3%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset. All scheduling variables in the robustness dataset refer to person-level averages over the full observation period, not previous four-week values.

NaN-values overview - Survival analysis dataset

Table 33: Missing values by country and role for the survival analysis dataset before NaN handling

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Dataset size						
Number of observations	6,402	1,853	43,393	35,760	4,592	1,602
Outcome and required model variables						
Duration of absence spell	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Returned-to-work event	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Employee profile						
Contract type	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Gender	0 (0.0%)	6 (0.3%)	534 (1.2%)	668 (1.9%)	0 (0.0%)	7 (0.4%)
Age	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Tenure at spell start	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Distance to work						
Distance to location	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Scheduling: total volume, previous 4 weeks						
Number of shifts in previous 4 weeks	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: weekday composition, previous 4 weeks						
Monday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Tuesday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Wednesday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Thursday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Friday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Saturday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Sunday shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: shift time, previous 4 weeks						
Morning shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Afternoon shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Evening shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Night shifts	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Scheduling: shift type, previous 4 weeks						
Ambient shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	

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Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Chilled shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Frozen shifts	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Operational/performance						
People per shift in previous 4 weeks	834 (13.0%)		3,447 (7.9%)		265 (5.8%)	
Picking/replenishing speed in previous 4 weeks	943 (14.7%)		4,857 (11.2%)		539 (11.7%)	
Driving score in previous 4 weeks		125 (6.7%)		3,325 (9.3%)		123 (7.7%)
Late shifts in previous 4 weeks	834 (13.0%)	122 (6.6%)	3,447 (7.9%)	3,187 (8.9%)	265 (5.8%)	123 (7.7%)
Leadership/team context						
Lead absence rate previous 4 weeks	15 (0.2%)	0 (0.0%)	1 (0.0%)	928 (2.6%)	4,592 (100.0%)	1,602 (100.0%)
Exogenous controls						
Influenza incidence	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Economic growth	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Major operational disruptions	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)

Note. Cells report the number of missing values with the percentage of observations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or are not present in the dataset. All scheduling variables refer to the previous four weeks.

I.4 Major Operational Disruptions

Table 34 provides an overview of the major operational disruptions included in the analysis. Disruptions were identified based on internal operational knowledge and included only when they were considered sufficiently substantial to potentially affect normal operations. National public holidays were excluded.

Table 34: Overview of major operational disruptions

Country	Operational disruption	Event period
The Netherlands		
NL	Snow and icy conditions; nationwide	16–19 January 2024
NL	Snow and icy conditions; Arnhem region	22 November 2024
NL	Storm Darragh; nationwide	6 December 2024
NL	NATO Summit and associated security and traffic restrictions; The Hague, Rotterdam and Leiden	22–26 June 2025
NL	SAIL Amsterdam; Amsterdam	20–24 August 2025
NL	Carnival; North Brabant and Limburg	10–13 February 2024
NL	Carnival; North Brabant and Limburg	1–4 March 2025
Germany		
DE	Farmers' protests; nationwide	8–15 January 2024
DE	Farmers' protests; Hamburg	29–30 January 2024
DE	Carnival; West & South Germany	10–13 February 2024
DE	Carnival; West & South Germany	1–4 March 2025
DE	UEFA European Football Championship; affected German host-city operations	14 June–14 July 2024
France		
FR	Farmers' protests; Paris	29 January–1 February 2024
FR	Paris Olympic and Paralympic Games and associated transport and security restrictions; Paris	15 July–8 September 2024
FR	Storm Kirk; Paris	9–10 October 2024
FR	"Bloquons tout" protests; nationwide	10 September 2025
FR	Nationwide strike	18 September 2025

Notes: Locations indicate the principal operational areas affected. National public holidays were excluded.

I.5 Descriptives

Absence rate OLS - Person-week level

Table 35: Descriptive statistics by country and role for the main OLS dataset

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Employee profile						
Fixed-term contract	0.496 (0.500)	0.336 (0.472)	0.921 (0.270)	0.972 (0.164)		
Permanent contract	0.503 (0.500)	0.664 (0.472)	0.078 (0.268)	0.027 (0.162)	1.000 (0.044)	1.000 (0.049)
Male	0.587 (0.492)	0.812 (0.391)	0.737 (0.440)	0.888 (0.316)	0.587 (0.492)	0.724 (0.447)
Female	0.413 (0.492)	0.188 (0.391)	0.263 (0.440)	0.112 (0.316)	0.413 (0.492)	0.276 (0.447)
Age under 26	0.179 (0.384)	0.640 (0.480)	0.347 (0.476)	0.591 (0.492)	0.510 (0.500)	0.667 (0.471)
Age 26–40	0.426 (0.494)	0.242 (0.428)	0.484 (0.500)	0.322 (0.467)	0.350 (0.477)	0.300 (0.458)
Age 40+	0.395 (0.489)	0.119 (0.323)	0.170 (0.375)	0.087 (0.281)	0.140 (0.347)	0.033 (0.178)
Tenure 0–93 days	0.021 (0.143)	0.017 (0.129)	0.673 (0.469)	0.700 (0.458)	0.825 (0.380)	0.776 (0.417)
Tenure 94–187 days	0.018 (0.133)	0.027 (0.162)	0.171 (0.377)	0.168 (0.374)	0.096 (0.295)	0.137 (0.344)
Tenure 188–365 days	0.068 (0.252)	0.041 (0.198)	0.093 (0.290)	0.100 (0.300)	0.053 (0.224)	0.063 (0.243)
Tenure 366–730 days	0.397 (0.489)	0.115 (0.319)	0.049 (0.216)	0.029 (0.168)	0.022 (0.147)	0.021 (0.143)
Tenure 731–1095 days	0.328 (0.469)	0.587 (0.492)	0.009 (0.094)	0.003 (0.055)	0.004 (0.063)	0.002 (0.045)
Tenure 1096–1460 days	0.053 (0.224)	0.115 (0.319)	0.002 (0.045)	0.000 (0.000)	0.000 (0.000)	0.001 (0.032)
Tenure 1461+ days	0.115 (0.319)	0.098 (0.297)	0.003 (0.055)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Distance to work						
Walking distance	0.098 (0.298)	0.368 (0.482)	0.157 (0.364)	0.256 (0.436)	0.026 (0.160)	0.211 (0.408)
Biking distance	0.424 (0.494)	0.511 (0.500)	0.444 (0.497)	0.572 (0.495)	0.374 (0.484)	0.579 (0.494)
Driving distance	0.478 (0.500)	0.121 (0.326)	0.399 (0.490)	0.172 (0.378)	0.600 (0.490)	0.210 (0.407)
Scheduling: total volume						
Total shifts in previous week	2.624 (1.799)	5.136 (3.592)	3.251 (1.664)	3.141 (2.427)	3.867 (1.846)	5.281 (3.856)
Paid hours in previous week	25.951 (11.458)	14.593 (9.373)	24.531 (11.055)	10.314 (5.841)	25.517 (12.881)	15.389 (9.086)
Scheduling: weekday composition						
Monday shifts	0.420 (0.422)	0.915 (1.006)	0.563 (0.378)	0.456 (0.575)	0.648 (0.393)	0.961 (0.984)
Tuesday shifts	0.386 (0.408)	0.776 (0.958)	0.533 (0.383)	0.570 (0.638)	0.625 (0.391)	0.889 (0.901)
Wednesday shifts	0.334 (0.386)	0.697 (0.918)	0.530 (0.383)	0.483 (0.581)	0.583 (0.387)	0.774 (0.832)

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Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Thursday shifts	0.443 (0.420)	0.691 (0.884)	0.577 (0.373)	0.493 (0.578)	0.677 (0.386)	0.793 (0.837)
Friday shifts	0.450 (0.425)	0.888 (0.937)	0.597 (0.376)	0.584 (0.637)	0.738 (0.381)	1.043 (0.958)
Saturday shifts	0.307 (0.384)	0.574 (0.825)	0.449 (0.338)	0.555 (0.618)	0.593 (0.362)	0.807 (0.780)
Sunday shifts	0.284 (0.380)	0.597 (0.875)	0.002 (0.024)	0.000 (0.001)	0.002 (0.023)	0.014 (0.121)
Scheduling: shift time						
Morning shifts	1.644 (1.902)	0.950 (1.291)	2.041 (1.720)	0.325 (0.611)	2.896 (1.806)	0.165 (0.441)
Afternoon shifts	0.942 (1.584)	2.049 (1.798)	1.155 (1.366)	1.169 (1.265)	0.971 (1.246)	2.046 (1.614)
Evening shifts	0.038 (0.228)	2.079 (2.153)	0.055 (0.427)	1.619 (1.452)	0.000 (0.044)	3.061 (2.453)
Night shifts	0.000 (0.000)	0.058 (0.164)	0.000 (0.003)	0.028 (0.120)	0.000 (0.000)	0.009 (0.060)
Scheduling: shift type						
Ambient shifts	1.508 (1.434)		2.071 (1.519)		2.275 (1.579)	
Chilled shifts	1.179 (1.233)		1.267 (1.252)		1.658 (1.351)	
Frozen shifts	0.189 (0.515)		0.180 (0.616)		0.220 (0.590)	
Operational/performance						
Driving score		91.977 (4.312)		91.321 (5.416)		89.613 (4.644)
Picking/replenishing speed	12.184 (17.935)		9.318 (10.859)		8.542 (6.988)	
Late shifts	0.102 (0.403)	0.247 (0.442)	0.415 (0.705)	0.188 (0.377)	0.392 (0.677)	0.615 (0.671)
People per shift	55.858 (40.661)		76.873 (47.945)		71.739 (47.846)	
Leadership/team context						
Captain absence rate previous 4 weeks	0.064 (0.039)	0.050 (0.084)	0.082 (0.042)	0.048 (0.061)	0.065 (0.045)	0.039 (0.088)
Average captain absence rate	0.064 (0.024)	0.049 (0.052)	0.085 (0.024)	0.048 (0.022)	0.058 (0.022)	0.039 (0.034)
Exogenous controls						
Influenza incidence	-0.263 (0.729)	-0.272 (0.720)	0.217 (1.198)	0.203 (1.190)	0.214 (0.990)	0.267 (0.993)
Economic growth	0.151 (0.139)	0.147 (0.142)	-0.033 (0.047)	-0.030 (0.046)	0.066 (0.074)	0.051 (0.061)
Major operational disruptions	0.057 (0.231)	0.059 (0.236)	0.018 (0.132)	0.015 (0.120)	0.078 (0.268)	0.070 (0.255)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country.

Absence rate OLS Robustness - Person level Robustness OLS Dataset

Table 36: Descriptive statistics by country and role for the robustness OLS dataset

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Employee profile						
Fixed-term contract	0.696 (0.460)	0.445 (0.497)	0.983 (0.131)	0.994 (0.075)	0.003 (0.050)	0.004 (0.067)
Permanent contract	0.304 (0.460)	0.555 (0.497)	0.017 (0.131)	0.006 (0.075)	0.997 (0.050)	0.996 (0.067)
Male	0.587 (0.493)	0.814 (0.389)	0.744 (0.437)	0.868 (0.339)	0.625 (0.484)	0.731 (0.443)
Female	0.406 (0.491)	0.184 (0.387)	0.253 (0.435)	0.129 (0.335)	0.375 (0.484)	0.269 (0.443)
Age under 26	0.266 (0.442)	0.710 (0.454)	0.449 (0.497)	0.656 (0.475)	0.596 (0.491)	0.695 (0.461)
Age 26–40	0.429 (0.495)	0.207 (0.406)	0.426 (0.495)	0.280 (0.449)	0.306 (0.461)	0.276 (0.447)
Age 40+	0.306 (0.461)	0.082 (0.275)	0.125 (0.331)	0.065 (0.246)	0.099 (0.298)	0.029 (0.168)
Tenure 0–93 days	0.021 (0.143)	0.017 (0.130)	0.665 (0.472)	0.691 (0.462)	0.785 (0.411)	0.732 (0.443)
Tenure 94–187 days	0.018 (0.131)	0.027 (0.161)	0.169 (0.375)	0.166 (0.372)	0.091 (0.288)	0.129 (0.335)
Tenure 188–365 days	0.068 (0.251)	0.041 (0.199)	0.092 (0.289)	0.099 (0.299)	0.050 (0.218)	0.059 (0.235)
Tenure 366–730 days	0.398 (0.490)	0.115 (0.319)	0.048 (0.215)	0.028 (0.166)	0.021 (0.142)	0.020 (0.139)
Tenure 731–1095 days	0.329 (0.470)	0.588 (0.492)	0.009 (0.093)	0.003 (0.058)	0.004 (0.061)	0.002 (0.041)
Tenure 1096–1460 days	0.053 (0.224)	0.115 (0.319)	0.002 (0.044)	0.000 (0.011)	0.000 (0.021)	0.001 (0.024)
Tenure 1461+ days	0.115 (0.319)	0.098 (0.297)	0.003 (0.051)	0.000 (0.015)	0.000 (0.000)	0.000 (0.000)
Distance to work						
Walking distance	0.114 (0.318)	0.389 (0.488)	0.143 (0.350)	0.238 (0.426)	0.047 (0.211)	0.199 (0.399)
Biking distance	0.430 (0.495)	0.493 (0.500)	0.441 (0.496)	0.576 (0.494)	0.300 (0.458)	0.586 (0.493)
Driving distance	0.456 (0.498)	0.118 (0.323)	0.416 (0.493)	0.186 (0.389)	0.653 (0.476)	0.215 (0.411)
Scheduling: total volume						
Total shifts per week	3.269 (1.136)	5.113 (2.809)	3.714 (0.982)	3.774 (1.755)	4.289 (0.845)	5.617 (2.624)
Average paid hours per week	24.065 (10.122)	12.754 (7.818)	21.133 (9.211)	9.857 (4.713)	23.274 (8.400)	14.377 (6.269)
Scheduling: weekday composition						
Monday shifts	0.463 (0.367)	0.872 (0.862)	0.654 (0.249)	0.554 (0.497)	0.717 (0.315)	0.940 (0.799)
Tuesday shifts	0.436 (0.358)	0.761 (0.821)	0.604 (0.273)	0.666 (0.538)	0.673 (0.319)	0.887 (0.745)
Wednesday shifts	0.373 (0.334)	0.653 (0.751)	0.601 (0.281)	0.547 (0.482)	0.606 (0.319)	0.761 (0.679)
Thursday shifts	0.488 (0.357)	0.632 (0.719)	0.644 (0.260)	0.528 (0.466)	0.728 (0.312)	0.747 (0.681)
Friday shifts	0.497 (0.359)	0.807 (0.770)	0.657 (0.257)	0.611 (0.503)	0.809 (0.273)	1.025 (0.791)
Saturday shifts	0.355 (0.343)	0.563 (0.728)	0.522 (0.237)	0.576 (0.481)	0.664 (0.300)	0.800 (0.655)

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Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Sunday shifts	0.335 (0.349)	0.623 (0.785)	0.002 (0.021)	0.000 (0.000)	0.003 (0.034)	0.024 (0.131)
Scheduling: shift time						
Morning shifts	1.774 (1.814)	0.888 (1.124)	2.304 (1.329)	0.317 (0.500)	3.171 (1.344)	0.154 (0.370)
Afternoon shifts	1.115 (1.563)	1.938 (1.497)	1.330 (1.089)	1.324 (1.081)	1.029 (1.049)	2.032 (1.292)
Evening shifts	0.058 (0.238)	2.024 (1.799)	0.052 (0.389)	1.811 (1.186)	0.000 (0.000)	2.987 (1.896)
Night shifts	0.000 (0.000)	0.060 (0.121)	0.000 (0.001)	0.031 (0.101)	0.000 (0.000)	0.010 (0.057)
Scheduling: shift type						
Ambient shifts	1.651 (1.199)		2.116 (1.116)		2.543 (1.068)	
Chilled shifts	1.231 (1.011)		1.025 (0.897)		1.472 (0.948)	
Frozen shifts	0.222 (0.477)		0.103 (0.387)		0.110 (0.277)	
Operational/performance						
Driving score		91.652 (4.443)		90.542 (6.848)		89.111 (4.703)
Picking/replenishing speed	14.341 (19.992)	0.000 (0.002)	9.389 (7.810)	0.009 (0.384)	8.678 (5.421)	0.000 (0.000)
People per shift	65.418 (33.232)	0.989 (0.308)	91.795 (34.892)	1.017 (2.861)	95.999 (36.273)	0.928 (0.275)
Late shifts	0.139 (0.363)	0.256 (0.339)	0.532 (0.625)	0.225 (0.308)	0.722 (0.739)	0.723 (0.554)
Leadership/team context						
Average captain absence rate	0.063 (0.024)	0.047 (0.052)	0.083 (0.023)	0.048 (0.024)	0.061 (0.022)	0.036 (0.034)
Exogenous controls						
Influenza incidence	-0.190 (0.387)	-0.204 (0.405)	0.325 (0.886)	0.224 (0.740)	0.222 (0.792)	0.302 (0.754)
Economic growth	0.159 (0.046)	0.156 (0.055)	-0.038 (0.043)	-0.037 (0.044)	0.066 (0.070)	0.052 (0.056)
Major operational disruptions	0.057 (0.053)	0.059 (0.063)	0.025 (0.093)	0.023 (0.092)	0.061 (0.154)	0.080 (0.182)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country. Outcome and exposure variables are excluded.

Survival Analysis Dataset

Table 37: Descriptive statistics by country and role

Variable	**NL Shopper**	**NL Runner**	**DE Shopper**	**DE Runner**	**FR Shopper**	**FR Runner**
Employee profile						
Temporary/flexible contract	0.726 (0.446)	0.547 (0.498)	0.973 (0.163)	0.995 (0.073)		
Permanent contract	0.274 (0.446)	0.453 (0.498)	0.027 (0.163)	0.005 (0.073)	1.000 (0.000)	1.000 (0.000)
Male	0.640 (0.480)	0.793 (0.405)	0.767 (0.423)	0.892 (0.311)	0.561 (0.496)	0.633 (0.482)
Female	0.360 (0.480)	0.207 (0.405)	0.233 (0.423)	0.108 (0.311)	0.439 (0.496)	0.367 (0.482)
Age under 26	0.237 (0.425)	0.640 (0.480)	0.469 (0.499)	0.645 (0.478)	0.581 (0.493)	0.682 (0.466)
Age 26–40	0.510 (0.500)	0.258 (0.438)	0.429 (0.495)	0.298 (0.457)	0.333 (0.471)	0.297 (0.457)
Age 40+	0.253 (0.435)	0.101 (0.302)	0.102 (0.302)	0.056 (0.231)	0.086 (0.281)	0.021 (0.142)
Tenure 0–93 days	0.010 (0.097)	0.017 (0.128)	0.461 (0.499)	0.381 (0.486)	0.426 (0.495)	0.382 (0.486)
Tenure 94–187 days	0.013 (0.114)	0.017 (0.130)	0.192 (0.393)	0.245 (0.430)	0.231 (0.422)	0.267 (0.442)
Tenure 188–365 days	0.053 (0.225)	0.049 (0.216)	0.194 (0.396)	0.230 (0.421)	0.208 (0.406)	0.245 (0.430)
Tenure 366–730 days	0.304 (0.460)	0.129 (0.335)	0.114 (0.318)	0.129 (0.335)	0.115 (0.319)	0.088 (0.283)
Tenure 731–1095 days	0.326 (0.469)	0.442 (0.497)	0.026 (0.159)	0.013 (0.113)	0.016 (0.126)	0.014 (0.119)
Tenure 1096–1460 days	0.118 (0.323)	0.203 (0.403)	0.005 (0.074)	0.001 (0.037)	0.004 (0.061)	0.004 (0.061)
Tenure 1461+ days	0.176 (0.380)	0.142 (0.350)	0.008 (0.087)	0.000 (0.016)	0.000 (0.000)	0.001 (0.025)
Distance to work						
Walking distance	0.093 (0.291)	0.373 (0.484)	0.156 (0.363)	0.253 (0.435)	0.034 (0.181)	0.240 (0.427)
Biking distance	0.448 (0.497)	0.513 (0.500)	0.458 (0.498)	0.574 (0.495)	0.371 (0.483)	0.529 (0.499)
Driving distance	0.459 (0.498)	0.114 (0.318)	0.386 (0.487)	0.173 (0.379)	0.595 (0.491)	0.230 (0.421)
Scheduling: total volume						
Number of shifts per week	3.123 (1.602)	6.144 (3.736)	3.583 (1.449)	3.676 (2.323)	4.364 (1.326)	6.662 (3.737)
Scheduling: weekday composition						
Monday shifts	0.471 (0.424)	1.172 (1.088)	0.602 (0.380)	0.580 (0.660)	0.729 (0.346)	1.338 (1.059)
Tuesday shifts	0.454 (0.420)	0.990 (1.041)	0.586 (0.383)	0.715 (0.707)	0.722 (0.340)	1.206 (0.960)
Wednesday shifts	0.407 (0.406)	0.868 (1.001)	0.587 (0.386)	0.580 (0.650)	0.657 (0.359)	1.004 (0.927)
Thursday shifts	0.545 (0.419)	0.873 (0.966)	0.649 (0.365)	0.576 (0.635)	0.752 (0.336)	1.009 (0.894)
Friday shifts	0.557 (0.424)	1.047 (0.993)	0.653 (0.368)	0.648 (0.678)	0.827 (0.301)	1.283 (0.977)
Saturday shifts	0.354 (0.405)	0.588 (0.845)	0.500 (0.364)	0.577 (0.641)	0.677 (0.334)	0.815 (0.775)
Sunday shifts	0.334 (0.404)	0.606 (0.886)	0.005 (0.071)	0.000 (0.000)	0.001 (0.019)	0.006 (0.071)

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Variable	NL Shopper	NL Runner	DE Shopper	DE Runner	FR Shopper	FR Runner
Scheduling: shift time						
Morning shifts	1.929 (1.944)	1.119 (1.388)	2.319 (1.698)	0.370 (0.657)	3.311 (1.602)	0.161 (0.422)
Afternoon shifts	1.144 (1.721)	2.531 (1.945)	1.211 (1.381)	1.404 (1.321)	1.053 (1.290)	2.505 (1.545)
Evening shifts	0.050 (0.266)	2.422 (2.246)	0.053 (0.419)	1.868 (1.438)	0.000 (0.000)	3.982 (2.491)
Night shifts	0.000 (0.000)	0.072 (0.209)	0.000 (0.000)	0.035 (0.159)	0.000 (0.000)	0.014 (0.091)
Scheduling: shift type						
Ambient shifts	1.625 (1.352)		2.020 (1.397)		2.232 (1.285)	
Chilled shifts	1.102 (1.141)		1.112 (1.133)		1.685 (1.195)	
Frozen shifts	0.173 (0.503)		0.130 (0.493)		0.207 (0.535)	
Operational/performance						
People per shift	64.144 (36.973)		84.979 (44.952)		79.583 (42.272)	
Picking/replenishing speed	11.837 (21.337)		9.749 (14.952)		9.501 (10.595)	
Driving score		91.798 (4.524)		90.932 (5.422)		88.912 (5.168)
Late shifts	0.125 (0.396)	0.285 (0.494)	0.540 (0.798)	0.218 (0.423)	0.468 (0.715)	0.653 (0.675)
Leadership/team context						
Lead absence rate	0.065 (0.041)	0.050 (0.089)	0.083 (0.042)	0.050 (0.068)	0.079 (0.000)	0.027 (0.000)
Exogenous controls						
Influenza incidence	-0.220 (0.776)	-0.160 (0.810)	0.280 (1.231)	0.295 (1.297)	0.176 (1.007)	0.331 (1.116)
Economic growth	0.146 (0.138)	0.142 (0.151)	-0.030 (0.046)	-0.028 (0.045)	0.071 (0.076)	0.060 (0.069)
Major operational disruptions	0.055 (0.228)	0.058 (0.234)	0.026 (0.160)	0.017 (0.128)	0.075 (0.263)	0.067 (0.251)

Note. Cells report means with standard deviations in parentheses. Empty cells indicate variables that are not applicable to the corresponding role or country.

Descriptive data

Table 35 presents the descriptive statistics for the main person-week OLS dataset, Table 36 presents the person-level robustness dataset, and Table 37 presents the absence-spell dataset used for the survival analysis. These tables should be interpreted together, but they do not describe exactly the same empirical population. The main OLS descriptives are based on employee-week observations, meaning that employees observed for more weeks contribute more strongly to the table. The robustness descriptives are aggregated at the employee level, meaning that each employee contributes one observation. The survival descriptives are based on observed sickness absence spells and therefore only describe the composition of employees with absence spell history rather than the full workforce. Consequently, the robustness table is most representative of the average employee, while the OLS and survival tables describe the average observed employee-week and sickness spell, respectively. This distinction is important when comparing patterns across tables.

The employee-profile variables show clear cross-country differences in contract structure. Germany is characterised by a predominantly fixed-term workforce, while France is almost entirely permanent in both the main OLS and robustness datasets. The Netherlands occupies a more mixed position, with both fixed-term and permanent contracts represented among Shoppers and Runners. This matches expectations, as within Picnic France only gives out permanent contracts, and Germany recently adopted this strategy, while Netherlands has a more tenure-based approach to contract types. Nevertheless, this contract composition is relevant for the later regression analysis, because contract type may capture both formal employment security and differences in worker attachment or selection.

Age and tenure also differ substantially across countries and roles. Dutch Shoppers have the oldest population, with the highest share of workers aged 40 and above and a relatively low share under 26. By contrast, France has the youngest workforce, especially in the person-level robustness dataset, where the under-26 share is particularly high for both Shoppers and Runners. The Netherlands also has the most tenured workforce. In Table 20, the share of employees with more than 731 days of tenure is much higher in the Netherlands than in Germany or France. This pattern remains visible in the robustness and survival descriptives, and matches Dutch Picnic contract policy. These differences suggest that cross-country comparisons should not be interpreted as policy differences alone, since they might also reflect substantial differences in workforce maturity. Gender composition is more balanced in the Netherlands and France, while Germany has the highest male share. This pattern is visible for both Shoppers and Runners in the OLS descriptives. However, the gender composition differs more strongly in the survival dataset, where the observed absence-spell sample is more male-heavy, especially among Runners. This reinforces importance of the difference in population per dataset.

The scheduling variables show strong role differences. Shoppers generally work fewer shifts. This indicates that the two roles differ not only in job content but also in exposure structure. Shift-time composition also differs clearly by role. Shoppers are more concentrated in morning and daytime work, whereas Runners are more exposed to afternoon and evening shifts. These descriptive differences support the decision to estimate separate models for Shoppers and Runners rather than pooling the two roles into one specification. There are also notable differences in weekday composition. Sunday work is mainly observed in the Netherlands, while Sunday shifts are close to zero in France and Germany. Friday is relatively prominent across several country-role groups. Night shifts are rare across all countries and roles, which means that night-shift coefficients in the regression models should be interpreted cautiously because they are based on limited variation.

Operational performance indicators also differ across countries. For Shoppers, picking/replenishment speed is highest in the Netherlands and lower in France and Germany. For Runners, the driving score is also highest in the Netherlands. However, the stronger performance indicators in the Netherlands may be related to its more experienced workforce and more established operations rather than higher individual effort alone. Lateness and staffing-context variables also show relevant operational differences that might relate to maturity. NL Shoppers have the lowest lateness exposure, while France shows relatively high lateness values, especially in the robustness descriptives. Among Runners, Germany often has the lowest lateness exposure, while France is higher.Larger Shopper teams in France and Germany may reflect differences in fulfilment-centre scale, demand, or staffing models. Similarly, Runners generally live closer to their work locations than Shoppers, which is consistent with the decentralised location of delivery hubs compared with larger fulfilment centres. These variables therefore capture broader organisational structures and should not be interpreted as isolated employee characteristics.

The exogenous variables show that the average influenza z-score is lower in the Netherlands than in France and Germany. Economic growth also differs by country: the Netherlands has positive average values, France is modestly positive, and Germany is negative in Table 20 and 21. Major operational disruptions are lowest in Germany and higher in the Netherlands and France. These differences justify including exogenous controls in the regression models, because part of the observed absence variation may reflect external conditions rather than only worker profile or operational context.

I.6 Duration & Frequency Distribution

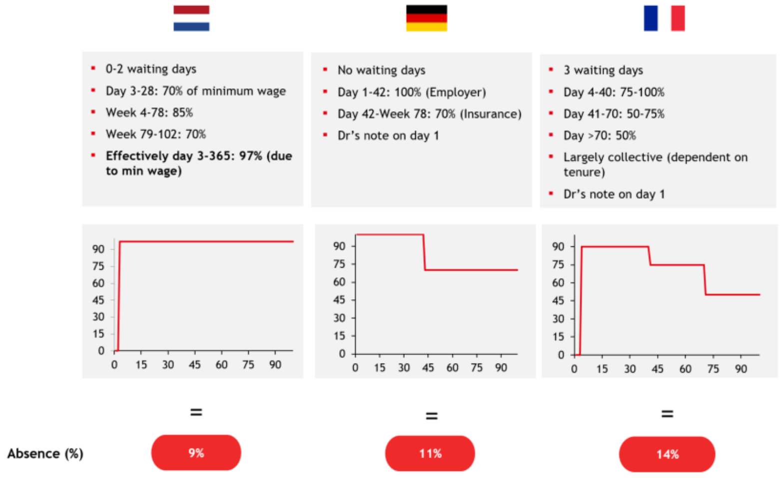


Figure 10: Policy vs absence rate

Duration distribution

Netherlands

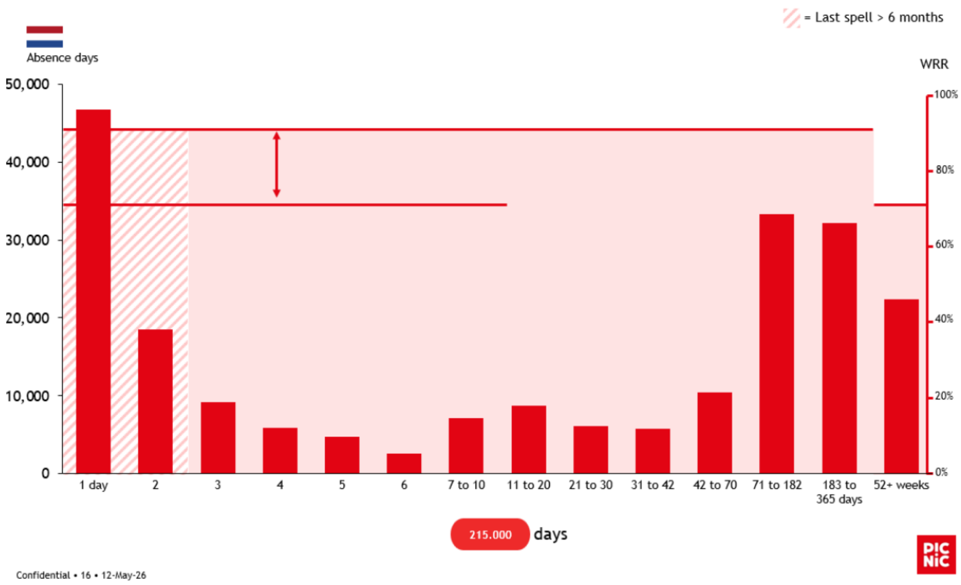


Figure 11: Dutch observed sickness absence days distribution.

Table 38: Dutch policy levers, expected absence patterns, and observed absence patterns

What?	**Where?**	**Expectations**	**Reality**
No Dr's note	-	High ST absence	High ST absence
0–2 waiting days	0–2 days	High/low ST absence	High ST absence*
70% WRR	3–10 days*	Mid absence	Low absence
97% WRR	11–70 days	High MT absence	Low absence
97% WRR	71–183 days	High LT absence	High absence
85% WRR	183+ days	High LT absence	High absence

The Dutch absence pattern is broadly consistent with several of the incentive propositions, but also shows clear deviations that require further decomposition. The most striking feature is the very high concentration of one-day absence. This pattern is consistent with the absence-threshold interpretation of short spells: in the Dutch implementation, there is no formal doctor's note requirement, and waiting days do not apply uniformly to all employees because workers without sickness absence in the previous six months face zero waiting days. The observed high level of one-day absence therefore appears consistent with a relatively low reporting threshold for short-term absence. At the same time, the low level of absence in the medium-term bins suggests that once spells extend beyond the very short-term margin, the Dutch pattern does not simply follow the relatively high effective wage replacement rate. Instead, absence days remain limited in the middle of the distribution. Long-term absence, however, is relatively high, especially in the longest duration categories. This is more consistent with the Dutch institutional structure, where employer wage-continuation obligations remain in place for up to 104 weeks. Overall, the Dutch system appears most vulnerable at two different margins: very short spells, where the absence threshold is low, and long-term spells, where income protection remains available for an extended period. To interpret this more precisely, additional plots should distinguish one- and two-day absences by whether waiting days actually applied, and should examine which employee characteristics are overrepresented in the short- and long-duration categories.

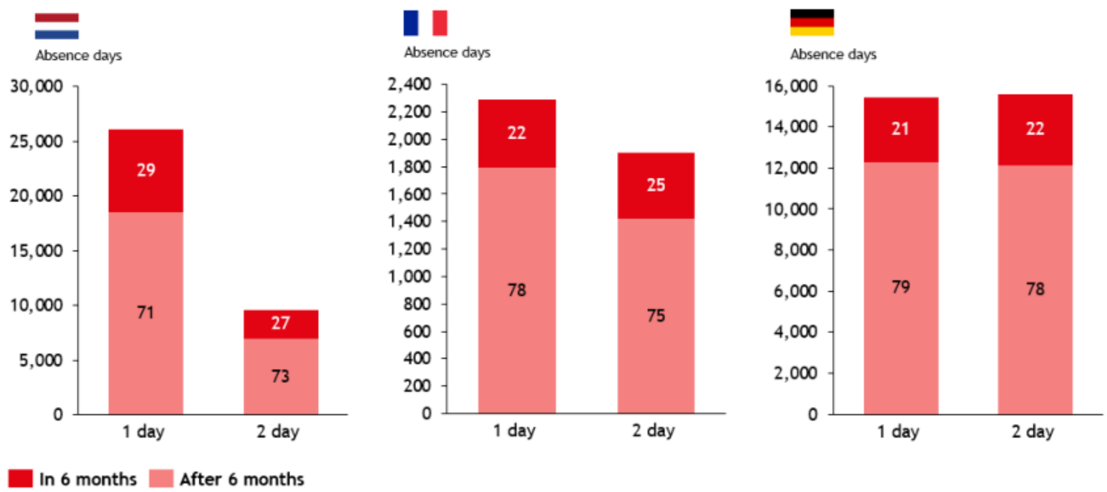


Figure 12: Application of Dutch waiting days

Figure 9 suggests that the Dutch waiting-day rule does not strongly discourage very short-term sickness absence. Employees within six months of a previous sickness spell, who are more likely to face waiting days, still account for a substantial share of one- and two-day absence. However, this group represents only around 30% of these short absences, meaning the waiting-day rule applies to a minority of cases. The conditional nature of the rule may therefore limit its deterrent effect, especially if employees do not clearly know whether waiting days apply or if the short-term reporting threshold remains low despite the potential financial cost.

Germany

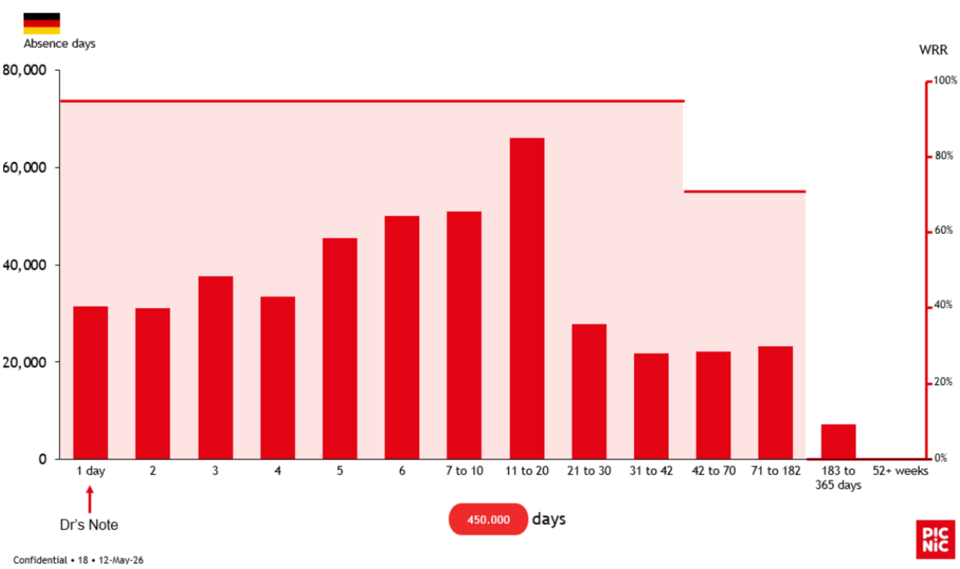


Figure 13: German observed sickness absence days distribution.

Table 39: German policy levers, expected absence patterns, and observed absence patterns

What?	**Where?**	**Expectations**	**Reality**
Dr's note	Day 1	Low ST absence	Mid ST absence
0 waiting days	-	High ST absence	Mid ST absence
100% WRR	0–10 days	High absence	High absence
100% WRR	11–42 days	High MT absence	High absence
70% WRR	43–182 days	Mid LT absence	Mid absence
0% WRR	183+ days	Low absence	Low absence

The German absence distribution is also broadly consistent with the proposed direction of the main policy levers, although the pattern is not uniform across all duration categories. The relatively low level of one-day absence compared with two-, three-, four-, and five-day absence may reflect the effect of the day-one doctor's note requirement for Shoppers and Runners. This suggests that the certification requirement may raise the reporting threshold for very short spells, especially where absence would otherwise be more discretionary or administratively easy to report. At the same time, Germany has no waiting days and provides full wage replacement during the first 42 days. The relatively high short- and medium-term absence burden is therefore consistent with a system in which the immediate financial cost of reporting sick is low and the income loss from remaining absent during the first six weeks is absent. The high concentration of absence in the 7–42 day range is particularly relevant from a policy-incentive perspective, because this is exactly the period in which employer-paid wage replacement remains at 100%. After day 42, the wage replacement rate decreases to the statutory sickness-benefit level, and observed absence becomes lower in the later duration categories, although long-term absence is still present. Overall, the German pattern suggests that the doctor's note may suppress the shortest spells, while the absence of waiting days and the 100% replacement rate appear aligned with relatively high short- and medium-term absence. Further analysis should examine which employee groups drive the medium-term burden, because the observed pattern may also reflect workforce composition, role differences, or recurrence among employees who already have a higher absence propensity.

France

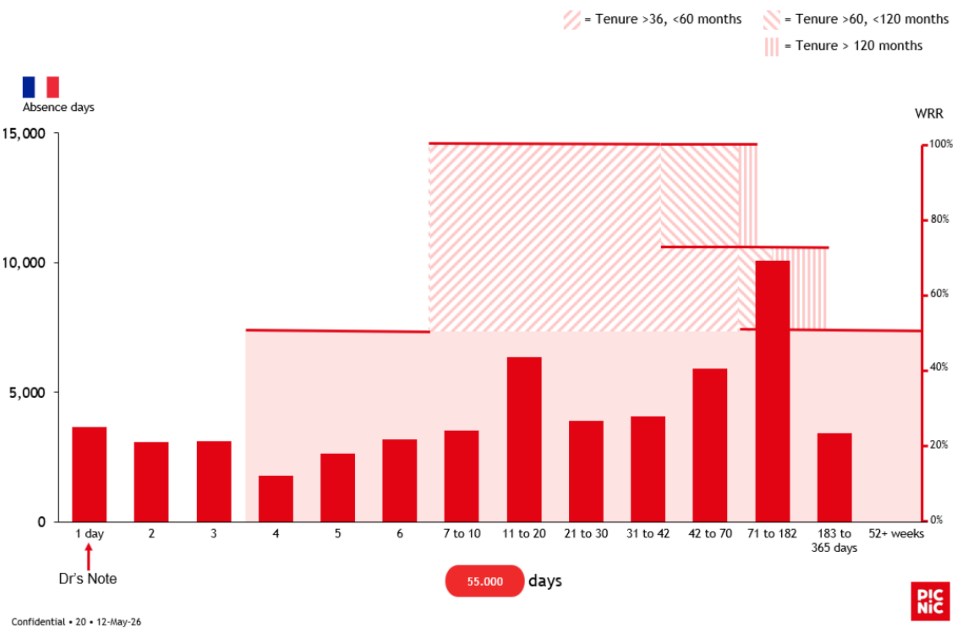


Figure 14: French observed sickness absence days distribution.

Table 40: French policy levers, expected absence patterns, and observed absence patterns

What?	**Where?**	**Expectations**	**Reality**
Dr's note	Day 1	Low ST absence	Low ST absence
3 waiting days	0–3 days	Low ST absence	Low ST absence
50% WRR	4–10 days	Mid absence	Mid absence
50% WRR	11–42 days	Mid MT absence	Mid absence
50% WRR	42–182 days	Mid LT absence	High absence
50% WRR	183+ days	High absence	Mid absence

The French absence pattern differs from both the Dutch and German cases, because the short-term threshold is stricter while the wage-replacement schedule is less generous for most operational employees. France combines a doctor's note requirement from day one with three waiting days. This creates both an administrative barrier and an immediate income loss at the start of a sickness spell. The relatively low observed absence volume in the first few days is therefore consistent with the expected effect of these short-term incentives: the French framework appears comparatively effective at limiting very short-term absence.

After the waiting period, most Shoppers and Runners rely mainly on statutory sickness benefit of around 50% wage replacement, unless they qualify for a tenure-dependent employer top-up. This makes the French medium-duration pattern more difficult to interpret. Based on the basic 50% replacement rate alone, one would expect relatively low absence volume after the first few days. The observed distribution partly follows this expectation in the early short-term bins, but absence increases in the 11–42 and especially the 43–182 day range. This suggests that the French pattern is not explained by the basic replacement rate alone.

One possible explanation is the tenure-dependent top-up structure, under which employees with sufficient seniority can receive more generous compensation for part of the spell. However, this explanation should be treated cautiously. If only a limited share of Picnic France's operational workforce has more than 36 months of tenure, then the top-up rules cannot explain the full observed medium- and long-duration burden. In that case, the high absence volume in the 43–182 day range is more likely to reflect other mechanisms, such as health severity, employee composition, role-specific working conditions, or recurrence among a smaller group of workers with longer spells.

The French distribution therefore supports the expected policy effect most clearly at the short-term margin. The combination of waiting days and day-one certification is aligned with relatively low one-day and early short-term absence. However, the relatively high absence volume between 43 and 182 days is less consistent with the low baseline wage-replacement rate and requires further decomposition. Overall, the French system appears comparatively strong at discouraging very short-term absence, but the medium- to long-duration margin remains important and cannot be explained by wage replacement alone.

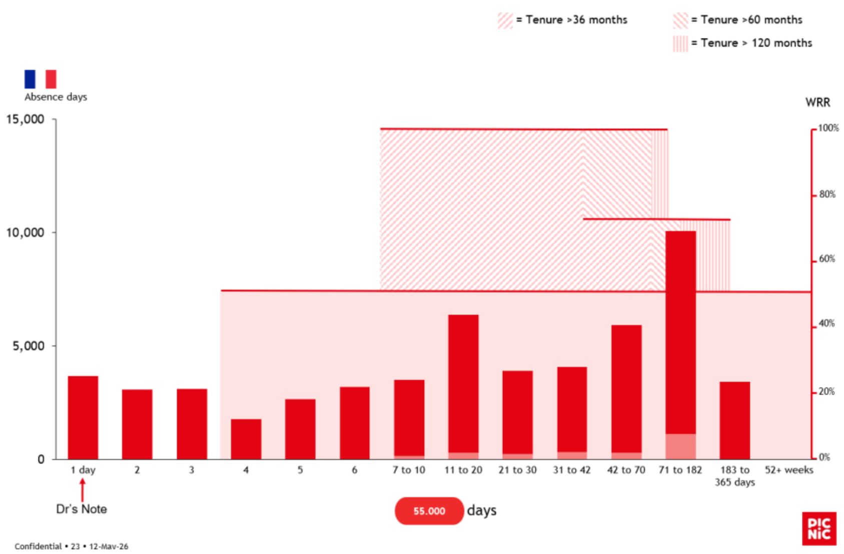


Figure 15: French tenure rules application

Table 41: French absence days by duration bin and tenure threshold

Days bins	**7–10**	**11–20**	**21–30**	**31–42**	**43–70**
Tenure > 36	44	0	165	123	165
Tenure > 60	0	0	0	0	0
Tenure > 120	0	0	0	0	0

The above tenure-threshold analysis suggests that the French medium-duration absence pattern is unlikely to be driven primarily by the formal tenure-based employer top-up rules. In theory, these rules could explain higher absence after the waiting-period stage, because employees with sufficient seniority may receive higher wage replacement for part of the spell. However, the observed absence days above the relevant tenure thresholds are very limited. Only a small number of absence days fall among employees with more than 36 months of tenure, while no observed absence days fall above the 60- or 120-month thresholds in the relevant duration bins. This means that the seniority-based top-up structure has little practical influence on the observed French absence distribution in this dataset. The higher absence volume in the 43–182 day range should therefore not be interpreted mainly as a policy-driven wage-replacement effect. A more plausible interpretation is that this part of the French distribution reflects other mechanisms, such as health severity, employee composition, role-specific working conditions, recurrence among a smaller group of workers, or adjustment and selection processes within the French operational workforce.

Frequency distribution

Where the previous exploratory analysis compared national social secrutity frameworks with absence duration distribution, this section will focus on absence frequency distribution per employee across the Netherlands, Germany, and France. This analysis focuses only on employees active in 2025 and relates the observed frequency distribution to two short-term policy levers: waiting days and doctor's note requirements. The expectation is that stricter short-term barriers should reduce absence frequency. More specifically, waiting days are expected to lower absence frequency by creating an immediate income loss when reporting sick, while doctor's note requirements are expected to reduce (discretionary) short-term absence by increasing the administrative burden and requiring proof of illness.

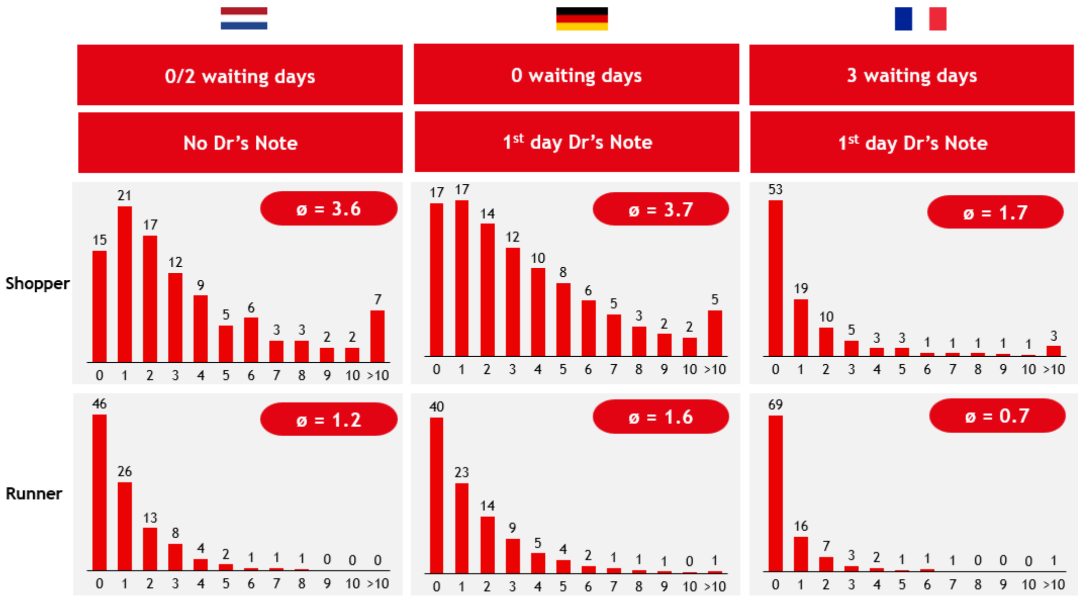


Figure 16: Observed absence frequency distribution

The observed pattern is broadly consistent with these propositions. France has the strictest short-term framework: three waiting days and a doctor's note requirement from the first day. It also shows the lowest average absence frequency for both roles. The average number of absence spells is approximately 1.7 for Shoppers and 0.7 for Runners. This suggests that the combination of direct financial cost and certification requirements is associated with fewer reported sickness spells. Especially for Runners, the French distribution is strongly concentrated around zero and one spell, indicating that repeated absence is relatively uncommon.

The Netherlands has a more permissive short-term framework. Waiting days vary between zero and two days depending on recent sickness history, and there is no formal doctor's note requirement. The Netherlands shows the highest average absence frequency, especially among Shoppers, with an average of approximately 3.6 spells per employee. Dutch Runners also show a relatively high average of approximately 1.2 spells per employee. This pattern is consistent with the expectation that the absence threshold is lower when there is no formal certification requirement and when waiting days do not apply uniformly to all workers.

Germany occupies an intermediate position. It has no waiting days, which would suggest a relatively low financial threshold for reporting sick. However, Shoppers and Runners are required to provide a doctor's note from the first day. The German averages are approximately 3.7 spells for Shoppers and 1.6 spells for Runners, placing Germany close to or above the Netherlands in average frequency depending on the role. This suggests that the doctor's note requirement alone does not fully offset the effect of having no waiting days. In other words, certification may reduce some short-term discretionary reporting, but without an immediate income loss, absence frequency can still remain relatively high.

Overall, the frequency distributions support the relevance of short-term policy levers. France, where both waiting days and day-one certification are present, has the lowest absence frequency. Germany and the Netherlands, where one or both of these barriers are weaker, show higher absence frequency. The comparison therefore suggests that the combination of waiting days and proof-of-illness requirements is more strongly associated with lower absence frequency than either lever in isolation. However, the result remains descriptive: differences in workforce composition, role structure, operational context, and employment patterns may also contribute to the observed cross-country differences.

I.7 Exploratory Determinant Analysis

Figuer 14 compares the distribution of sick-leave days across duration bins for Shoppers and Runners. The figure shows that the two operational roles differ not only in overall absence level, but also in the shape of the duration distribution. Shoppers show a relatively stronger concentration in very short spells, especially around one-day absence, while Runners show more weight in intermediate duration bins. This suggests that the two roles may be associated with different absence mechanisms. Shopper absence appears more concentrated around short-term reporting behaviour, whereas Runner absence seems more strongly connected to somewhat longer spells. These differences may reflect differences in job content, physical demands, operational responsibility, scheduling, replacement possibilities, or workforce composition. Because of this role-level heterogeneity, pooling Shoppers and Runners into one regression model would risk masking important differences. The exploratory evidence therefore supports the decision to estimate separate models by employee type.

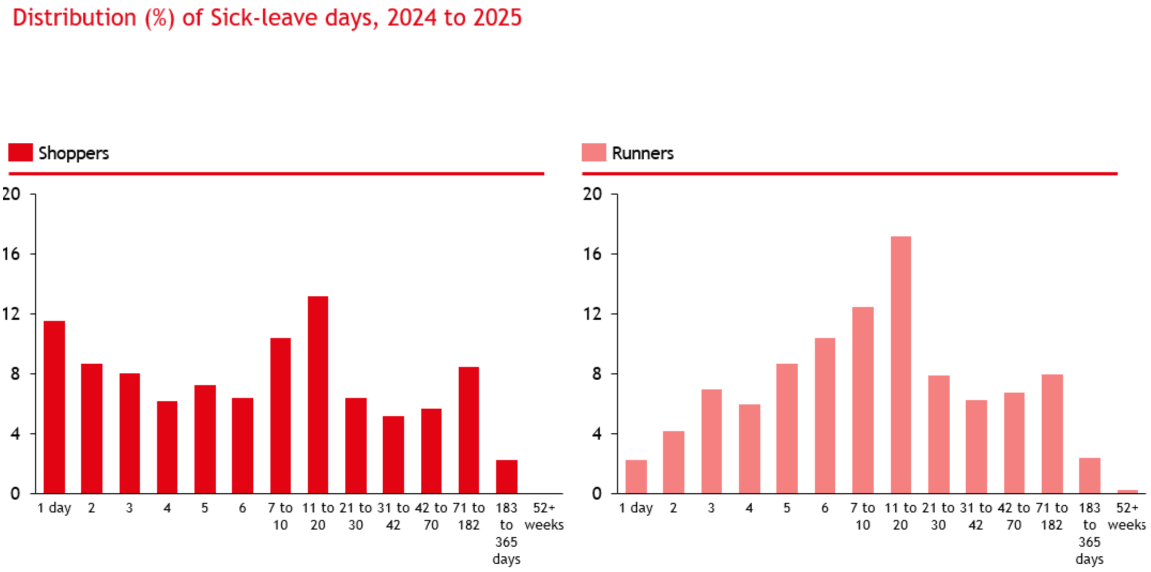


Figure 17: Observed sickness absence days distribution per role.

The location-level plots in appendix I further show that sickness absence varies substantially across fulfillment centres and hubs within the same country. This is important because it shows that national policy cannot be the only relevant explanation. If policy were the dominant driver, absence patterns would be expected to be relatively similar within each country. Instead, the location plots suggest that local operational conditions, site management, team composition, staffing pressure, or local workforce characteristics may also shape absence behaviour. This justifies the inclusion of job-context and operational variables in the regression models and suggests that country comparisons should be interpreted cautiously unless within-country variation is also considered.

The contract-type duration plot in Appendix I shows that permanent contracts are associated with longer average sickness absence durations than fixed-term contracts in the Netherlands and Germany. This pattern is consistent with the idea that employment security may affect the absence threshold: employees with permanent contracts may perceive less employment risk when reporting sick or remaining absent, whereas fixed-term employees may experience stronger implicit attendance pressure. However, Figure 15 shows that the relationship with the overall absence burden is not uniform. In the Netherlands, permanent employees have both a higher absence rate and longer average spells, while in Germany permanent employees have longer spells but a lower absence rate than fixed-term employees. No direct comparison can be made for France because the fixed-term category is not observed in the plotted data. Contract type should therefore not be interpreted as a single mechanism. It may also capture differences in age, tenure, role attachment, work experience, or health selection. These descriptive plots support including contract type as an employee-profile control variable, while leaving its interpretation to the multivariate analyses.

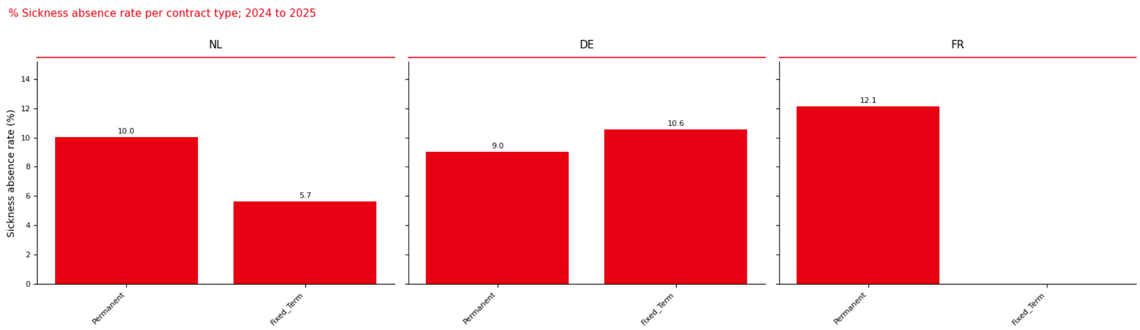


Figure 18: Sickness absence rate per contract-type per country.

The age plots in Appendix I show two different patterns depending on whether absence is measured by duration or absence rate. Average spell duration generally increases with age, especially among Runners, suggesting that older employees may take longer to return once a sickness spell has started. This is consistent with the idea that older workers may experience fewer but more persistent health-related absence episodes. However, the absence-rate plots show a more non-linear pattern: younger groups often display higher absence rates, while some older groups have lower overall absence rates despite longer average spell durations. This reinforces the importance of distinguishing between absence occurrence, overall absence burden, and spell duration. In the regression models, age should therefore be included using categories rather than assuming a simple linear relationship.

Figure 30 in appendix I shows relatively modest differences. Female Runners have a slightly higher sickness absence rate than male Runners, while among Shoppers the difference is smaller and appears to run in the opposite direction. This suggests that gender is relevant as a control variable, but it does not appear to be one of the dominant explanatory factors in the exploratory data. The role-specific direction of the difference also suggests that gender effects may partly depend on workforce composition and job context rather than reflecting a uniform relationship with sickness absence.

Figure 16 shows a clearly non-linear relationship between tenure and sickness absence rate. For both roles, absence does not simply increase or decrease with longer employment duration. Among Runners, absence rates are relatively high in some early and later tenure groups, while the middle-tenure group shows lower absence. Among Shoppers, absence rates decline after the first months but rise again among longer-tenured workers. This pattern may reflect several mechanisms at once: adjustment effects among newer employees, selection effects among those who remain employed, changing job attachment, accumulated exposure, or changes in contract security over time. The plot therefore supports treating tenure categorically in the regression models rather than as a continuous linear variable.

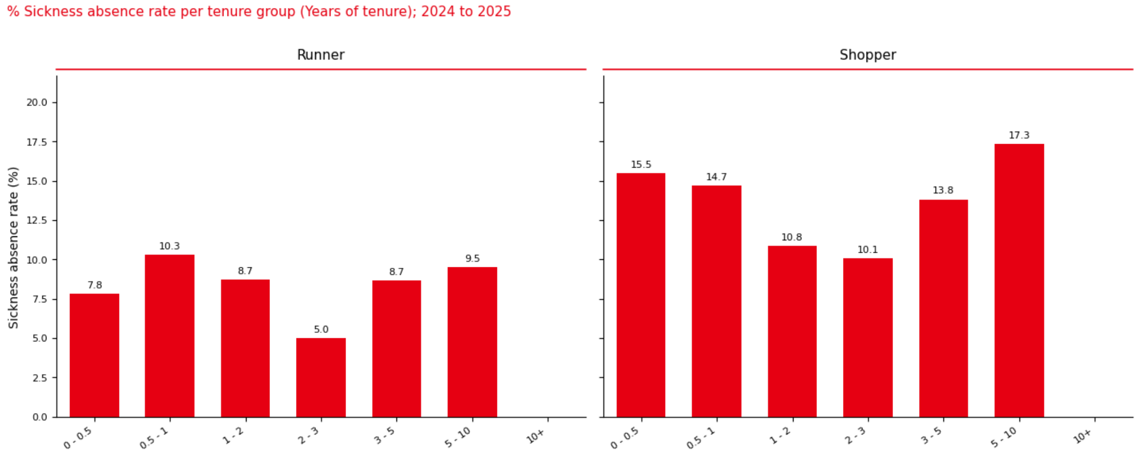


Figure 19: Sickness absence rate per tenure-group per country.

Figure 17 shows that commuting distance is more strongly related to absence rate than to average spell duration. Figure 33 in Appendix I shows that average absence duration differs only slightly between the 0–2 km, 2–10 km, and 10+ km groups, especially among Shoppers. However, the absence-rate plot above shows clearer differences. This should be interpreted cautiously, because the observations in this plot are binned. The same applies to the other binned scatter plots used in this section: binning reduces noise and can make relationships appear more pronounced than they are at the individual-observation level. For Runners, absence is lowest in the 2–10 km group and higher among both the closest and furthest commuters. For Shoppers, employees living within 0–2 km show the highest absence rate, while the 2–10 km and 10+ km groups are lower and relatively similar. This pattern should not be interpreted as a direct commuting-burden effect only. Short commuting distance may also capture student populations, urban workforce composition, site-specific labour pools, or role-specific selection. Nevertheless, the observed differences justify including commuting distance as a categorical employee-profile variable.

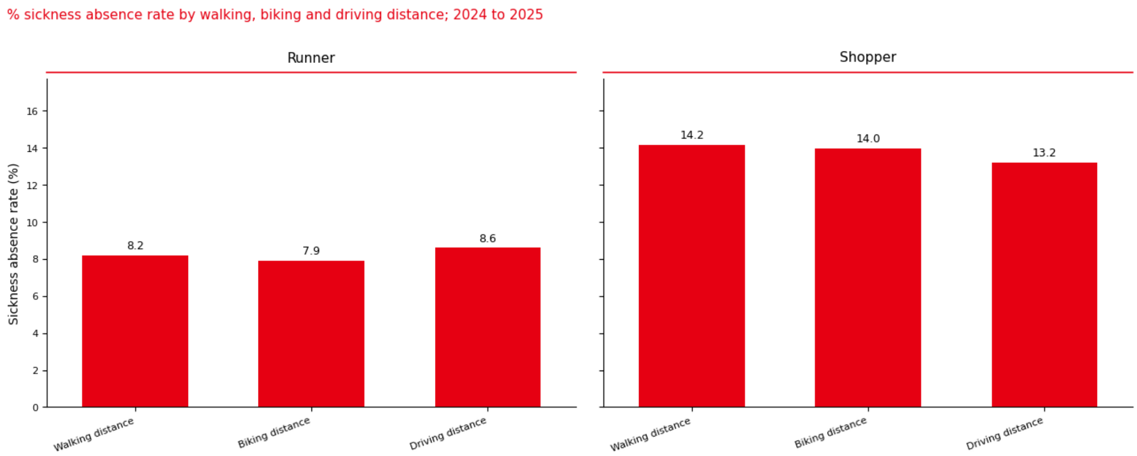
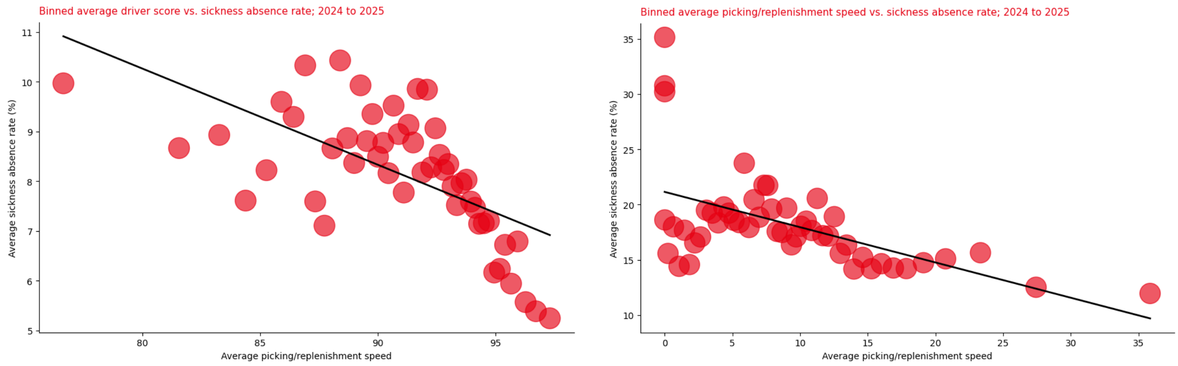


Figure 20: Sickness absence rate per commuting category per country.

Figure 18 provides additional evidence that individual and operational characteristics are related to sickness absence. The binned relationship between picking/replenishment speed and absence rate suggests a negative association: employees with higher picking or replenishment speed tend to have lower absence rates. This may indicate that more experienced, more attached, or better-performing workers are less frequently absent. However, reverse interpretation is also possible: employees with more absence may have less stable work routines or fewer observed hours from which performance is measured. The relationship should therefore be interpreted as an association, not as evidence that higher speed directly reduces sickness absence.



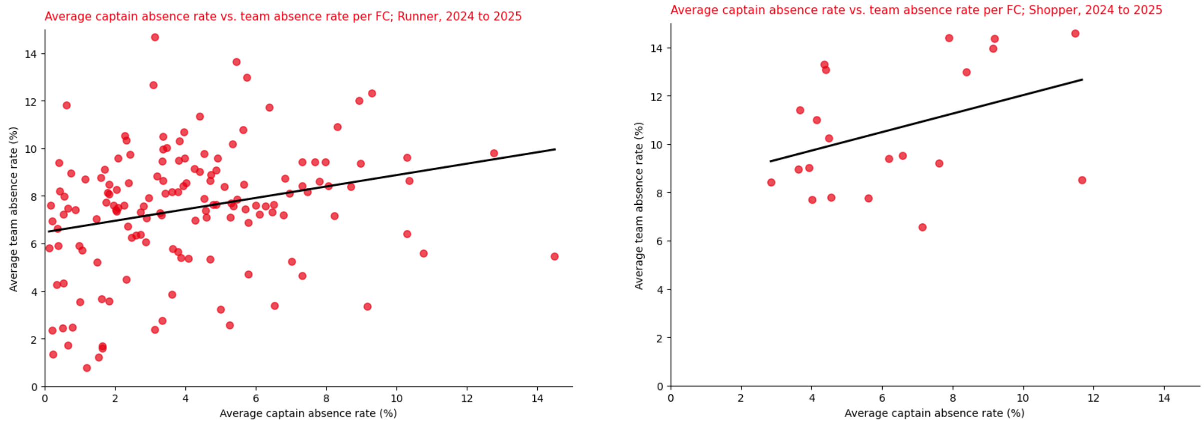
(a) Sickness absence rate vs. Driver score

(b) Sickness absence rate vs. Picking/replenishing speed

Figure 21: Sickness absence rate by role-specific performance indicators

Figure 34 in appendix I shows a positive relationship between staffing context and absence rate. Higher average people per shift is associated with higher absence in the exploratory plot. This may reflect larger or busier locations, more complex operations, or site-level staffing practices rather than a direct effect of team size itself. It may also indicate that absence is partly clustered in larger operational environments where replacement capacity and reporting norms differ. This supports including people per shift as an operational-context variable, while controlling for other role and location characteristics.

Figure 35 in appendix I show that the association between late-shift exposure and sickness absence is not uniform. In one plot, late-shift exposure appears weakly positively related to absence, while in another the association is negative. This suggests that late shifts should not be interpreted as a simple universal risk factor. Their relationship with sickness absence may depend on role, country, scheduling structure, employee selection into late shifts, or the type of workers who are available for these shifts. The exploratory evidence therefore supports including late-shift exposure in the regression models, but interpreting it together with role-specific and country-specific results.



(a) Runner team sickness absence rate vs. Captain sickness absence rate

(b) Shopper team sickness absence rate vs. Captain sickness absence rate

Figure 22: Team sickness absence rate by Captain sickness absence rate

Also, Figure 19 shows a positive relationship between team absence and team lead absence. This is one of the clearest indications that absence may cluster within local organisational units. Several mechanisms could explain this pattern. High lead absence may reflect broader site-level pressure, weak team continuity, reduced supervision, or shared working conditions. Alternatively, both lead absence and team absence may be driven by the same underlying site-level factors, such as workload, staffing shortages, local management conditions, or workforce composition. The plot does not identify which mechanism dominates, but it clearly supports including lead or captain absence and colleague absence as job-context variables in the empirical models.

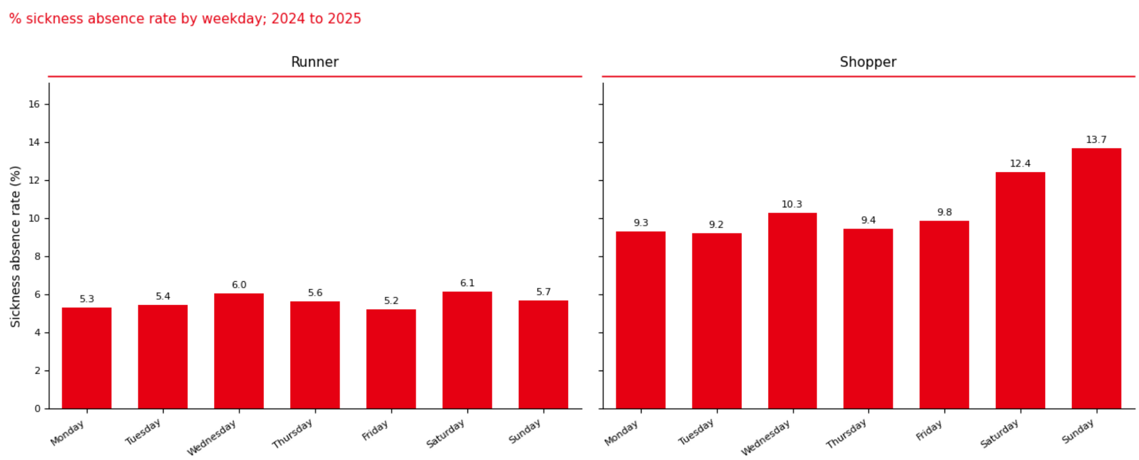


Figure 23: Sickness absence rate per weekday per role

Figure 20 suggests that sickness absence is related to the weekday composition of recent work, but the pattern differs strongly between roles. For Runners, absence rates are relatively stable across the week, ranging from 5.2% on Friday to 6.1% on Saturday. This suggests that weekday timing is not a major descriptive differentiator for Runner absence, although Saturday is slightly higher. For Shoppers, the pattern is more pronounced. Weekday absence rates are lower from Monday to Friday, ranging from 9.2% to 10.3%, while Saturday and Sunday show substantially higher absence rates of 12.4% and 13.7%. This may indicate that weekend work is associated with higher absence among Shoppers, possibly because weekend shifts differ in workload, employee composition, availability constraints, or motivation. However, the plot should be interpreted descriptively only: higher weekend absence does not necessarily mean that weekend work causes sickness absence, because employees scheduled on weekends may systematically differ from weekday workers.

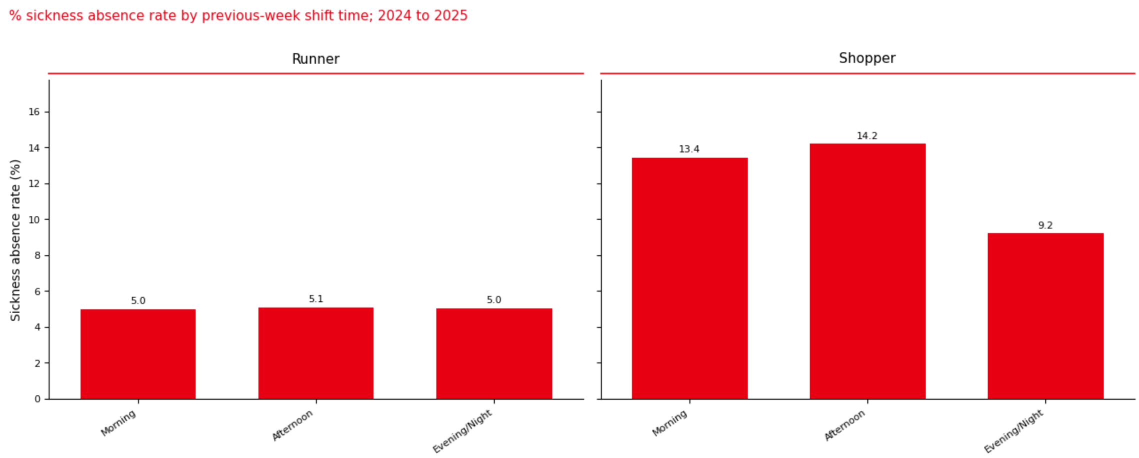


Figure 24: Sickness absence rate per shift-time per role

Figure 21 provides further evidence that scheduling context is related to sickness absence, again mainly for Shoppers. For Runners, absence rates are almost identical across shift times, with morning, afternoon, and evening/night shifts all around 5.0% to 5.1%. This suggests that, descriptively, Runner absence is not strongly differentiated by time of day. For Shoppers, however, absence is higher for morning and afternoon shifts. This could reflect differences in the type of employees working these shifts, differences in shift availability, or operational differences between daytime and evening work. It should therefore not be interpreted as evidence that evening or night shifts reduce absence. Instead, the pattern suggests that shift-time composition may capture relevant employee-selection and scheduling differences that should be controlled for in the regression models. Because planning data such as shift-time and shift-type only exists for weeks in which workers were expected to work, not in weeks where they were already sick the absence rates are a bit distored in these plots. The absence rates are generally lower because of this.

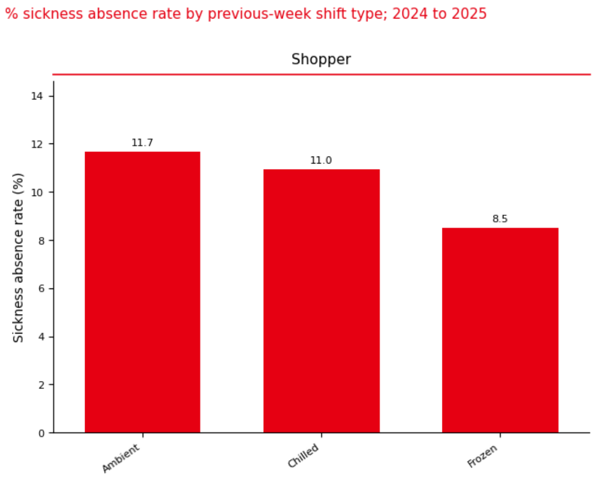


Figure 25: Sickness absence rate per shift-type

Figure 22 focuses on Shoppers and shows that sickness absence also differs by operational work area. Ambient shifts have the highest absence rate, at 11.7%, followed by chilled shifts at 11.0%, while frozen shifts have the lowest absence rate at 8.5%. At first sight, this is not necessarily what would be expected if physically or environmentally demanding work directly increased absence, since frozen work could plausibly be considered more demanding. A more likely explanation is that shift type also captures selection into work areas, differences in team composition, experience, or the amount of exposure employees have to each department. Employees working frozen shifts may, for example, be a smaller or more stable subgroup. Therefore, this plot suggests that shift type is relevant for understanding Shopper absence patterns, but it should be interpreted as an operational association rather than a causal effect of the temperature zone itself. This fits the thesis setup where scheduling and shift-type variables are treated as job-context variables in the empirical models.

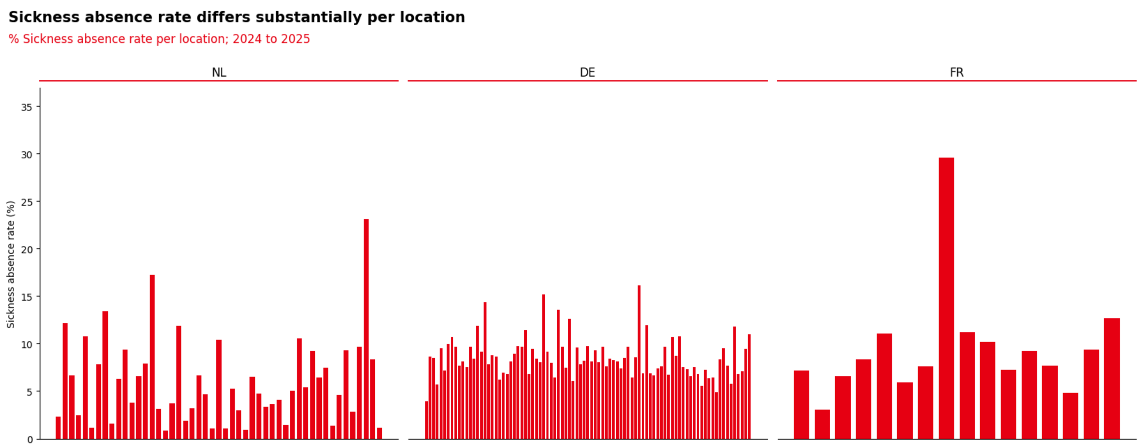


Figure 26: Sickness absence rate per Hub

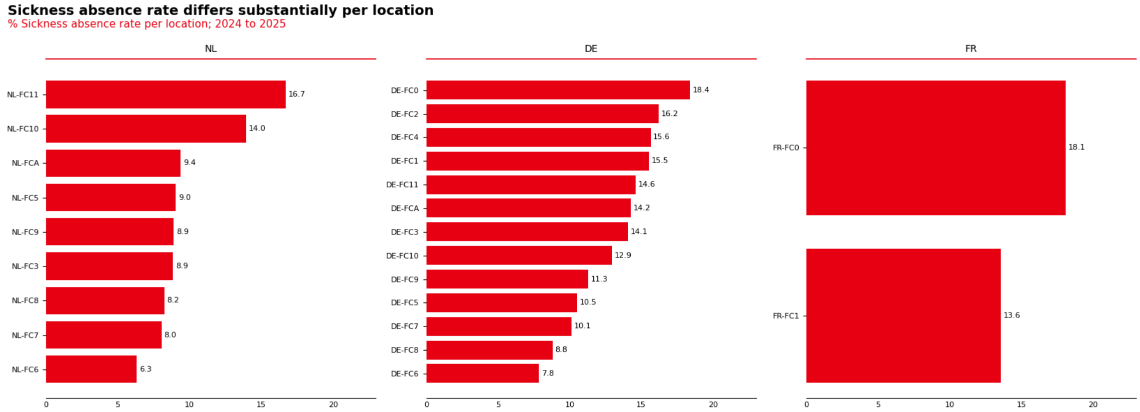


Figure 27: Sickness absence rate per FC

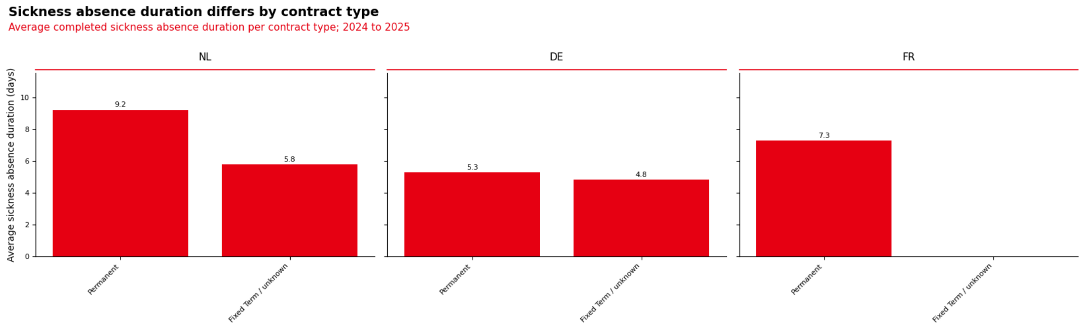


Figure 28: Sickness absence duration per contract-type

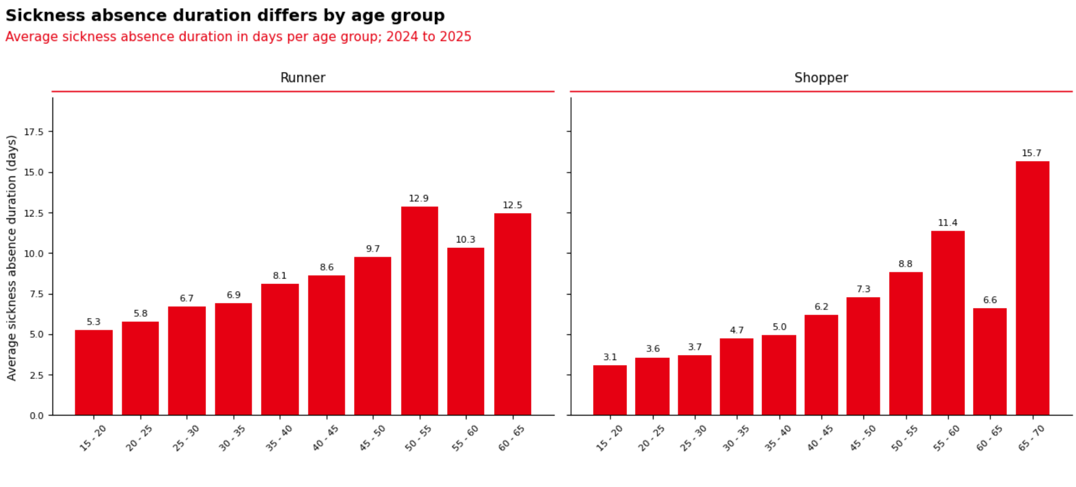


Figure 29: Sickness absence duration per age category

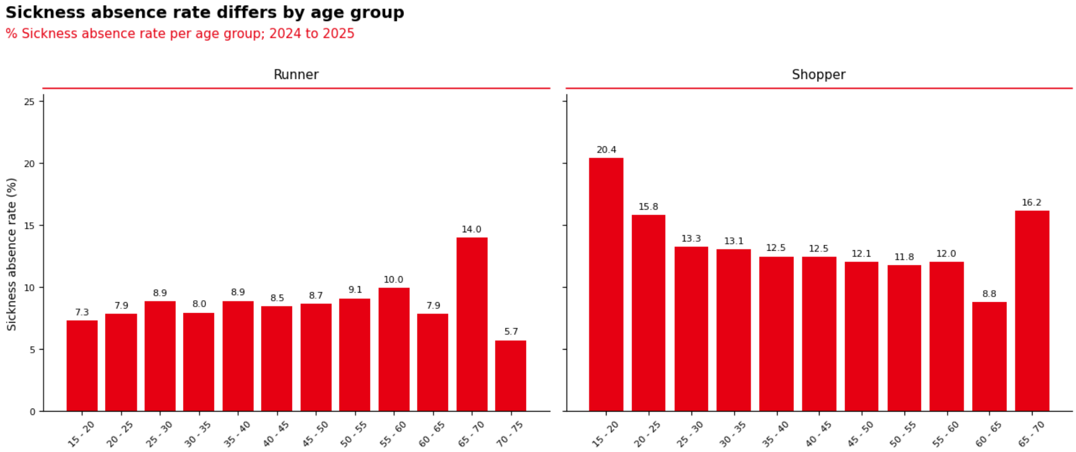


Figure 30: Sickness absence rate per age category

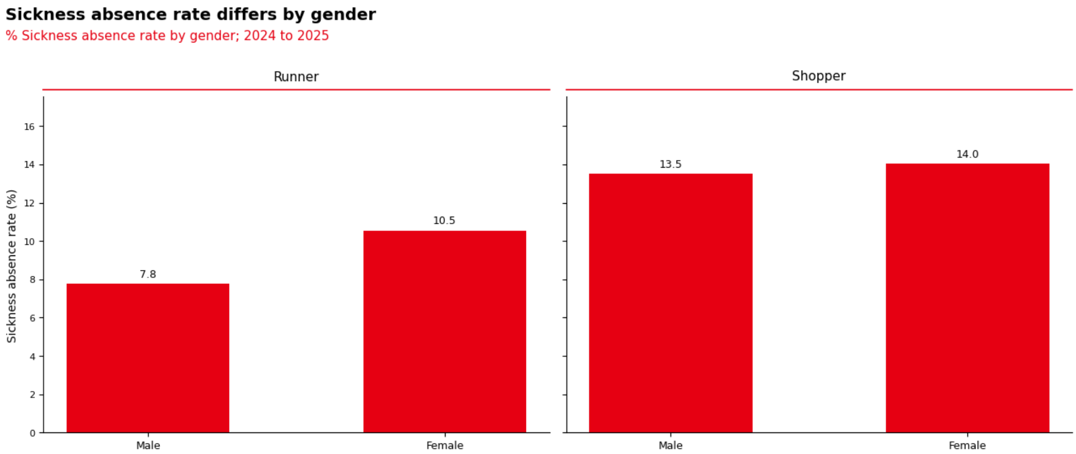


Figure 31: Sickness absence rate per gender (m/f)

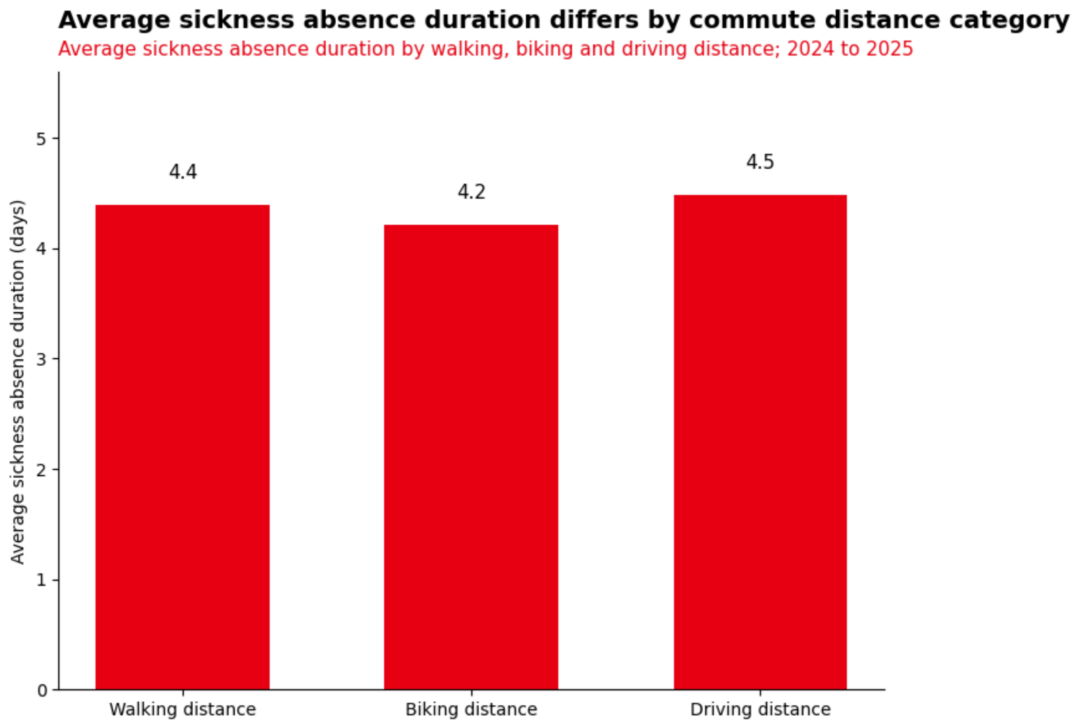


Figure 32: Sickness absence rate per commuting distance category

Figure 33: Sickness absence rate vs. People per shift

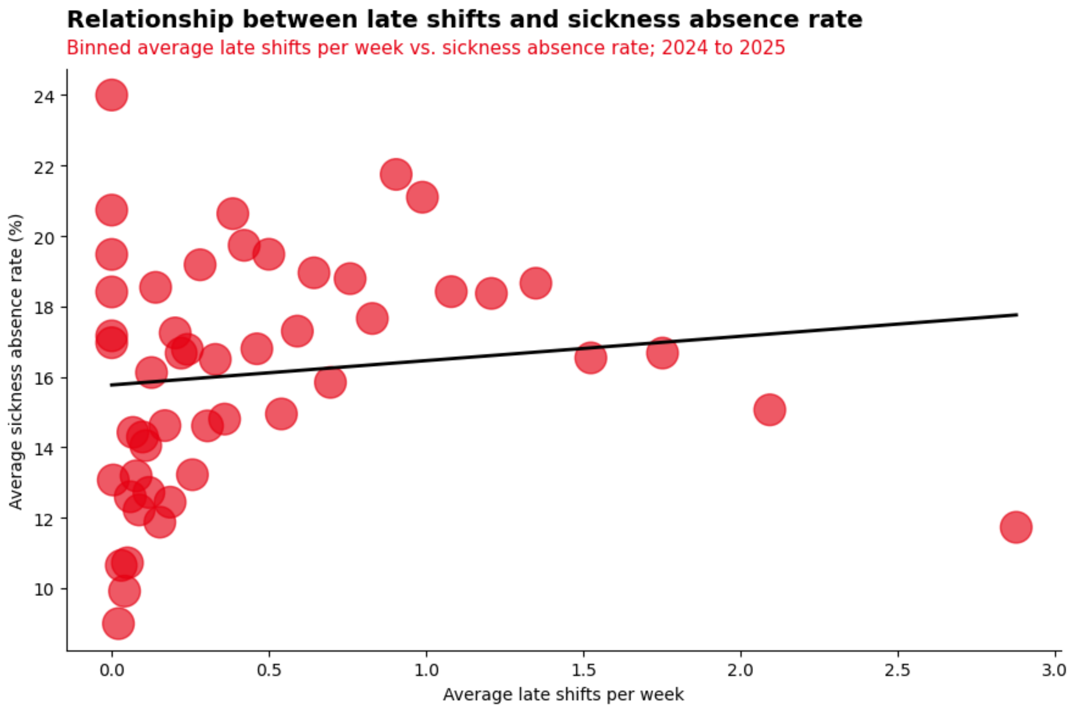


Figure 34: Sickness absence rate vs. Lateness

I.8 Kaplan-Meier Curves

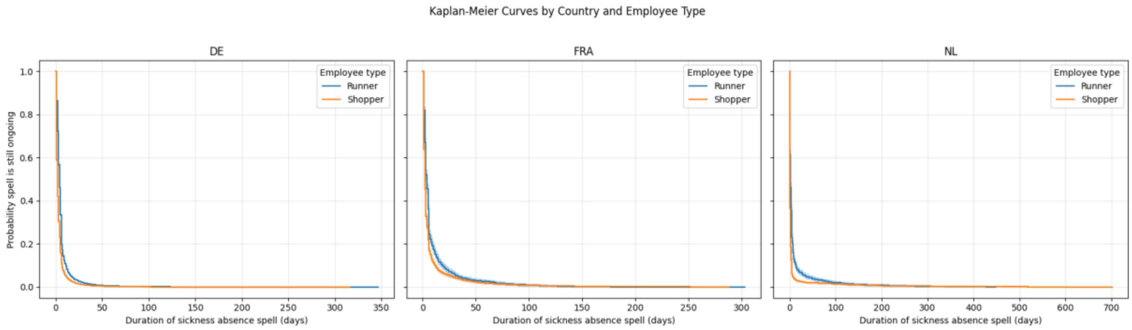


Figure 35: Kaplan-Meier curves per role per country

Overall, the curves show that sickness absence duration is strongly concentrated at short durations. In all country–employee type groups, the survival probability drops sharply during the first days of absence, indicating that a large share of sickness spells end quickly. After this initial decline, the curves flatten close to zero, meaning that only a relatively small proportion of spells continue for longer periods. This pattern suggests that the distribution of sickness absence duration is highly right-skewed, with many short spells and a small number of long-duration spells.

The country-specific curves show broadly similar patterns, but differ in the length of the tail. France shows a relatively short tail, with the probability of a spell still being ongoing approaching zero after approximately 100 to 200 days. Germany follows a similar pattern, although some longer spells are still present. The Netherlands shows the longest observed spell durations. In the Dutch sample, Runner spells continue beyond 400 days, while Shopper spells extend up to around 700 days. This indicates that long-term sickness absence is particularly relevant in the Dutch data, even though most spells also end within a relatively short period.

When comparing employee types, the differences are more modest than the country-level differences. Shopper spells generally decline slightly faster than Runner spells, especially in the early part of the curves. This suggests that, conditional on a sickness spell having started, Shoppers tend to return somewhat sooner than Runners. Conversely, Runner curves remain slightly higher for parts of the duration range, indicating that Runner absence spells are somewhat more likely to last longer. However, these differences vary by country and should be interpreted as descriptive patterns rather than causal effects. The Dutch Shopper curve also contains the longest observed outliers, suggesting that while most Shopper spells are short, a small number of very long spells remain present.

I.9 Operational Recommendations

Operationally, the recommendations for logistics are based on a common principle: absence interventions should be tailored to the specific absence margin and to the institutional and operational context in which it occurs. In the Netherlands, very short-term absence should be addressed through stricter employee selection and availability checks for Friday shifts. Plus, practical measures such as better preparation for chilled- and frozen-zone work, suitable clothing. Long-term Dutch absence requires a different response. Because this margin appears to interact with the long-term Dutch social security framework, the logistic sector should focus on reducing the risk that absence becomes persistent once it starts. This means giving more preventive and reintegration attention to older workers, monitoring sickness absence among longer-tenured employees more carefully, and evaluating whether permanent contracts are allocated in a way that supports sustainable work attachment and return-to-work behaviour.

In Germany, the priority is local operational diagnosis. The results suggest that German absence is shaped not only by the early-stage wage-replacement framework, but also by operational variation such as people per shift, local captain absence context, lateness, performance indicators, and disruptions. logistics should therefore focus on site-level differences in captain team oversight, also more thorough assessment in captain selection, being stricter on lateness and performance, as well as better oversight during disruptions. These recommendations might not only be relevant in Germany. Similar relationships may also exist in the Dutch and French operations, but may have been harder to detect because of smaller samples. Further analysis of these factors in the Netherlands and France would therefore be valuable before ruling them out as operational levers.

In France, the priority is not generic absence control, because strict short-term barriers already appear to suppress very short-term reporting. The tenure-related absence pattern suggests sickness absence rises for tenured employees, which might be related to motivation and job fit. Therefore, the main operational focus should be talent retention and Shopper workforce development. Logistics should examine whether early- and medium-tenure Shoppers receive sufficient support, whether the job matches expectations, and whether local operational conditions contribute to absence among this group.

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