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Company Decisions Under Uncertainty and Inertia in Consumer Choice

Kaido Kepp

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Declaration:
Hereby I declare that this doctoral thesis, my original investigation and achievement, submitted for the doctoral degree at Tallinn University of Technology has not been submitted for doctoral or equivalent academic degree.

Kaido Kepp

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Ettevõtete otsused ebakindluse tingimustes ja inerts tarbijate valikutes

KAIDO KEPP

TALTECH KIRJASTUS

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List of Publications

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Author’s Contribution to the Publications

The author's contributions to the papers in this thesis are as follows:

I Kaido Kepp: Conceptualisation (supporting); Data collection and initial assembly (lead); Literature review – first draft (lead); Writing – results and conclusions (supporting); Validation (equal); Writing – review and editing (supporting). Prof. Kadri Männasoo: Conceptualisation (lead); Data curation and investigation (lead); Methodology (lead); Software (lead); Formal analysis (lead); Validation (equal); Visualisation (lead); Writing – review and editing (lead); Corresponding author.

II Kaido Kepp: Conceptualisation (lead); Data collection and assembly (lead); Literature review – lead; Formal analysis (equal); Methodology (lead); Writing – first draft (lead); Writing – review and editing (lead); Corresponding author. Karin Jõeveer: Data curation (supporting); Formal analysis (equal); Validation (equal); Writing – review and editing (supporting).

III Kaido Kepp: Conceptualisation (lead); Data collection and assembly (lead); Literature review – first draft (lead); Methodology (supporting); Validation (equal); Writing – review and editing (equal); Corresponding author. Kadri Männasoo: Methodology (lead); Data curation (lead); Formal analysis (lead); Validation (equal); Writing – review and editing (equal).

Introduction

Economic agents – whether individual consumers or companies – operate under substantial uncertainty regarding the outcomes of their decisions and choices. Although their specific contexts differ, both types of agents are governed by common principles of rationality, risk preference, and the strategic use of information. Each also exhibits a form of 'stickiness': consumers display inertia in repeated choices, while companies face irreversibility in capital commitments (the inability to costlessly undo investments once made). At the core lies a shared trade-off between acting immediately and waiting for better information. In the consumer domain, this trade-off is formalised as rational inattention; for companies, it appears as the option value of waiting under investment irreversibility.

In microeconomics, a foundational distinction is made between risk (where the probabilities of future states are known) and uncertainty (where they are not) (Knight, 1921)[1]. Most economic models focus on decision-making under risk, assuming agents can assign subjective probabilities to uncertain events. The empirical identification problems that arise from this distinction are discussed in the methodology sections below.

Within this framework, both companies and consumers must allocate scarce resources – such as capital, income, or cognitive effort – towards actions with uncertain payoffs. Resource optimisation under uncertainty is therefore the central analytical problem. A rational agent acquires information only when its expected benefit exceeds its cost. For companies, sunk costs and managerial beliefs about the macroeconomic environment may exacerbate status quo bias (Samuelson & Zeckhauser, 1988) and lead to deferred investment (Bernanke, 1983), potentially harming financial performance. This setting provides the framework of the thesis and is depicted in Figure 1.

While the specific objectives and constraints of companies and consumers differ, the underlying principles are similar. Both entities maximise an objective function (profit or utility) based on subjective probabilities of future events. Their choices are shaped by their attitude toward risk, their susceptibility to behavioural biases, and market or informational frictions. These features jointly determining the speed and completeness of agents' adjustment to changing conditions.

The optimal amount of information to process is reached when the marginal benefit of an additional piece of information – the improvement it brings to the decision – equals its marginal cost in terms of time, money, or cognitive effort. Below this threshold, gathering more information improves outcomes; beyond it, the agent is better off deciding on the basis of what they already know. In practice, this means that a company will not monitor every competitor's pricing move, and a consumer will not compare every available insurance offer – not because they are irrational but because selective inattention is itself the rational response to scarce cognitive resources.

[1] For a more recent overview and less restrictive handling of risk and uncertainty, please see Holton (2004).

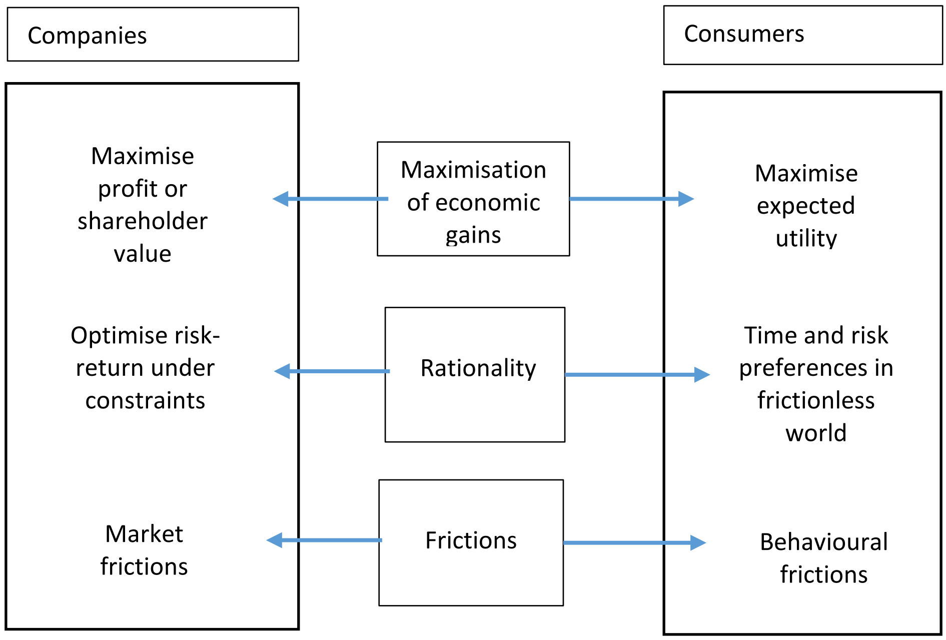

Figure 1. The setting of economic decisions by companies and consumer choices studied in the thesis. Compiled by the Author.

From the company side, a large body of work has explored how irreversibility and macroeconomic uncertainty affect the volume and timing of investment (Bernanke, 1983; Dixit & Pindyck, 1994; Caggese, 2007; Guiso & Parigi, 1999; Schauer, 2019), often using survey-based measures or single-country samples that focus on capital formation rather than realised financial performance. What remains largely unquantified is how different types of investment (fixed vs current) and accompanying debt flows translate into risk-adjusted profitability measures, such as ROA and ROIC, across the business cycle in a broad cross-country micro dataset.

From the consumer side, empirical studies of inertia in markets such as health, electricity, telecommunications, and car insurance have typically operated in environments where the relevant choice sets are incomplete or only partially observed, and where monetary search and switching costs between different service providers are non-trivial. Switching costs here refer to the monetary and non-monetary costs a consumer incurs when changing service providers, including administrative effort, loss of accumulated loyalty and learning, and psychological costs of change. This definition follows Klemperer (1987, 1995). When switching costs are present, they complicate the disentangling of attention or search frictions from genuine switching frictions and make it difficult to separate learning from unobserved heterogeneity when only limited information on offers and claims is available.

The research gap at the thesis level therefore consists of two missing elements in the extant literature. First, on the company investment side, prior literature has failed to provide large-sample micro evidence on how cyclical adversity, fixed asset investment irreversibility, and financial flows interact to shape risk-adjusted company-level performance. In addition, it remains unclear whether there are non-linear thresholds in macro adversity beyond which fixed investment becomes particularly detrimental. Second, on the consumer side, existing empirical work has rarely combined fully observed, repeated choice sets with minimal monetary switching costs and rich after-the-accident-claim information. Doing this would allow a cleaner separation of attention versus choice frictions and a more precise analysis of learning from different types of insurance claims. The thesis addresses this gap through three empirical essays using EU manufacturing company data and Estonian car insurance data.

On this basis, the thesis formulates three main research questions that map directly to its three empirical articles.

Research Question 1 (Article I): How does cyclical adversity (periods of negative output gaps and elevated price volatility, as defined in Kepp & Männasoo, 2021) interact with irreversible fixed investment, current investment, and debt flows to shape risk-adjusted financial performance of European manufacturing companies?

Research Question 2 (Article II): What triggers consumer switching in car insurance when full information and low monetary switching costs are present, and how do different types of insurance claims affect switching behaviour, using Estonian broker data with fully observed offer sets?

Research Question 3 (Article III): To what extent is consumer inertia in car insurance driven by attention frictions, as opposed to choice preferences, in a quasi-experimental setting with fully observed offers and negligible pecuniary switching costs?

For Research Questions 2 and 3, car insurance is a particularly well-suited setting for studying consumer inertia for several reasons. First, it is an annual, semi-compulsory, and rather homogeneous product, and, in our setting, the coverage is standardised, the renewal decision is regular, and the stakes are well defined. Second, insurance is a classic 'experience good' (Nelson, 1970): quality (i.e. the insurance claim settlement process) is only revealed after a claim event, creating an information asymmetry that motivates initial inertia and enables the study of learning. Third, in the Estonian broker-mediated leasing context, the consideration set of offers is fully observed by the researcher, which is rare in empirical work and allows clean identification of attention versus choice frictions without imputing unobserved alternatives.

The research questions stated above guide the structure of the thesis. Article I focuses on company-level investment decisions and performance under cyclical adversity in EU manufacturing, drawing on company-level panel data from the Orbis Europe database assembled as part of this doctoral research and covering 10,190 manufacturing companies across 24 EU member states over 2005–2018. Article II turns to the consumer side and examines switching behaviour and learning from claims in the Estonian car insurance market, a setting in which choice sets are fully observed and monetary switching costs are negligible. It provides reduced-form evidence on the triggers of switching, which in turn motivates the structural analysis in Article III. Article III represents the methodological centrepiece of the consumer-focused essays. Using the same institutional setting, it decomposes consumer inertia into attention and choice components within a two-stage structural framework. The quasi-experimental data-generation process – featuring standardised, fully observed offer sets – enables precise and separate identification of attention frictions and choice determinants.

Taken together, the three articles deliver a unified insight that would not emerge from any of them alone: that the dominant friction suppressing welfare-improving action is not the absence of attractive alternatives for companies or consumers but the elevated cost of acting on information that is already available. This shared conclusion has a common policy implication developed in Section 4.

The thesis employs two datasets and three econometric methods, as detailed in Section 2. Article I applies Dynamic System-GMM to an EU manufacturing panel from Orbis Europe. Articles II and III use a proprietary dataset from the largest insurance broker in Estonia. Article II employs panel Logit and Linear Probability Models, while Article III estimates a Two-Stage Discrete Choice Model using GMM.

Theoretical background

1.1 Companies' investment decisions under uncertainty

In the neoclassical ideal of frictionless markets, a manufacturing company's investment decisions are governed by the pursuit of an optimal capital stock, where the marginal productivity of capital equals its user cost as a static optimisation. Within this theoretical framework – often associated with Jorgenson's (1963) neoclassical model and the Modigliani-Miller theorem – the company's financial performance is independent of its capital structure and of the specific timing of its investments, provided those investments have a positive Net Present Value (NPV). In such a world, invested capital is perfectly reversible: manufacturing equipment, specialised machinery, and production facilities can be bought or sold in deep secondary markets without significant transaction costs or price discounts.

A related formulation, Tobin's *q* – defined as the ratio of a firm's market value to the replacement cost of its capital stock (Tobin, 1969) – provides an equivalent optimality condition: investment should proceed when q exceeds unity, reflecting that the market values an additional unit of capital above its cost of reproduction. Hayashi (1982) established the conditions under which marginal and average *q* are equivalent, making the empirical literature operational. Together, Jorgenson's user cost approach and *q* theory form the twin pillars of the neoclassical investment framework.

Within this frictionless context, the theoretical relationship between investment and uncertainty is counterintuitive. Foundational models developed by Hartman (1972) and Abel (1983) predict that uncertainty in output prices can increase investment. This occurs because the marginal revenue of capital is modelled as a convex function of the output price. Under the assumption of perfect competition and the ability to flexibly adjust labour and other inputs relative to capital, an increase in price volatility raises the expected value of the marginal revenue of capital. Essentially, in a frictionless manufacturing sector, companies can fully exploit high-price episodes while costlessly shedding capital during downturns, making volatility a potential driver for increased capital formation rather than a deterrent.

However, even within the neoclassical tradition, this smooth relationship begins to break down once adjustment costs are introduced. Caballero and Engel (1999) show that when adjustment costs are non-convex, investment occurs in 'lumps' rather than as a continuous flow. As a result, the smooth relationship between Tobin's *q* and investment weakens. Their work on lumpy capital investment provides a natural bridge to the irreversibility literature discussed in the next section, as lumpiness and partial irreversibility often co-exist in manufacturing settings characterised by specialised equipment and long installation lags.

The introduction of irreversibility fundamentally transforms the investment problem. Suppose that a portion of the capital outlay is a sunk cost that is unrecoverable in resale markets without a significant discount. In that case, investing today entails forgoing the opportunity to act on information that may arrive tomorrow. This forgone opportunity is the option value of waiting, which acts as an additional hurdle beyond the standard NPV threshold: a project must not only be profitable but sufficiently profitable to compensate for destroying the option (Pindyck, 1991).

The size of this option value depends on three key determinants (Pindyck, 1991). First, the degree of irreversibility: the higher the sunk-cost share, the greater the value of waiting, as exiting a mistimed investment becomes more costly. Second, the level of uncertainty: the option value increases convexly with the volatility of the underlying project value; a mean-preserving spread in future profitability raises the value of waiting because the downside is bounded by sunk costs, while the upside remains open. Third, the investment trigger threshold: irreversibility drives a wedge between the NPV-break-even point and the actual investment trigger, so that firms require returns that substantially exceed the cost of capital before committing. Abel, Dixit, Eberly, and Pindyck (1996) formalise this by modelling installed capital as a portfolio of two options – specifically, options to expand and to abandon. Higher uncertainty raises the threshold for expansion and lowers the threshold for exit, creating a range within which neither investing nor divesting is optimal. This 'band of inaction' is a central implication of irreversible investment models.

This concept provides a useful lens for interpreting the empirical results in Article I of this thesis. The output gap range of −1% to −3%, within which the adverse performance effects of fixed investment become significant, is consistent with firms operating within or near such a band. In this region, firms are unable to expand profitably, but also unable to exit without incurring losses, so that past irreversible investments generate the largest realised underperformance. The exact boundaries of this band are determined by model parameters including the sunk-cost share, the discount rate, and the volatility of returns. The empirical thresholds identified in Article I should therefore be understood as reduced-form evidence consistent with this mechanism, rather than as a direct calibration of the theoretical model.

Dixit (1992) extends this logic by showing that irreversibility can generate hysteresis. Because the thresholds for entry and exit diverge, an economy can remain stuck well away from its optimal capital stock long after the original shock has dissipated, a dynamic that helps explain the prolonged investment depression observed in European manufacturing following the 2008–2009 and 2011–2012 crises.

Taken together, these insights establish the frictionless neoclassical benchmark and show how the introduction of irreversibility changes investment behaviour in a fundamental way. They provide the basis for analysing the role of irreversibility, financial constraints, and macroeconomic conditions in the empirical sections that follow.

1.1.1 Irreversible corporate investment under uncertainty and credit constraints

Abrupt shifts in aggregate demand and market liquidity – such as those observed during the 2008–2009 Global Financial Crisis and the subsequent Sovereign Debt Crisis – where the timing of investment significantly affects risk-adjusted financial performance.

The European manufacturing sector is particularly exposed, having experienced a decline in global competitiveness relative to emerging economies (Marschinski & Martinez Turegano, 2019). While declining competitiveness does not automatically translate into higher uncertainty, it increases the variance of future demand and pricing outcomes. As firms face more volatile market share dynamics and less predictable revenue streams, aggregate uncertainty rises. In this setting, investment decisions can no longer be viewed as purely internal choices but must be understood as conditional on the broader macroeconomic environment.

Against this backdrop, economic theory remains divided on how uncertainty influences investment. Traditional models (Hartman 1972, Abel 1983), as discussed in Section 1.1., suggest a positive investment-uncertainty relationship under perfect competition. This prediction changes, however, once irreversibility is introduced. In this framework, firms hold a 'real option' to wait. Investing today eliminates this option and removes the possibility of learning from future information that may reveal a project to be unprofitable. As a result, the option value of waiting rises with uncertainty, strengthening the incentive to delay investment.

This dynamic is heavily influenced by the macroeconomic environment. Chen and Funke (2010) show that as the economy shifts between states (e.g., boom, recession, or turmoil), the investment thresholds required to trigger action rise dramatically, confirming that macroeconomic instability acts as a major deterrent to investment. Intuitively, when firms cannot reliably predict which regime will prevail – whether a current downturn is temporary or the onset of prolonged turmoil – the option value of waiting exceeds the expected return from immediate investment. Investments that would have been undertaken at modest expected returns in stable periods are postponed, as firms require substantially higher returns to compensate for the risk of irreversible losses. As a result, aggregate investment may remain depressed long after the initial shock has passed, as firms wait for clearer macroeconomic signals.

This effect is not uniform across all capital goods. Early empirical work often treated investment as a homogeneous category, but later research by Guiso and Parigi (1999) and Schauer (2019) highlights asset-specific irreversibility. Schauer (2019) uses unique survey data to distinguish between capacity expansion investments and non-capacity investments. Capacity expansion – such as establishing new production sites or hiring additional workers – involves substantial planning and sunk costs, making it highly irreversible. By contrast, non-capacity investments, including replacement, rationalisation, and restructuring, primarily maintain or upgrade existing capital without expanding capacity, and are therefore less irreversible.

Consistent with this distinction, Schauer (2019) finds that a rise in uncertainty leads to a statistically and economically significant decrease in capacity expansion investments, while having no significant effect on non-capacity investments like replacement or rationalisation. This suggests that the negative relationship between investment and uncertainty observed in aggregate data is driven almost entirely by the most irreversible components of a company's capital.

Recent studies have extended Schauer's insight in two important directions. Drakos and Tsouknidis (2024), studying investment in ocean-going commercial vessels – a setting characterised by high-value, highly specific real assets – confirm that heightened uncertainty reduces both the probability of investment and the size of spending conditional on triggering. Importantly, they show that these effects are amplified when the secondary market for vessels is illiquid, providing direct evidence that the degree of asset reversibility, measured through resale market conditions, modulates the uncertainty–investment relationship. They further find that this amplifying effect operates through global economic uncertainty, rather than sector-specific earnings uncertainty, highlighting that the type of uncertainty matters for the irreversibility channel. This distinction aligns with the dual measurement approach used in Article I of this thesis. The intuition for this finding is that global economic uncertainty affects the option value of all assets simultaneously: when the entire economy is uncertain, there is no safe haven to which capital can be redeployed, making the inability to exit the current investment especially costly. By contrast, sector-specific earnings volatility may be partially hedged or diversified across industries, muting its impact on the irreversibility premium.

In a methodologically distinct contribution, Kumar, Gorodnichenko, and Coibion (2023) use randomised information treatments in a survey of New Zealand firms to generate exogenous variation in perceived macroeconomic uncertainty. They find that higher uncertainty leads firms to reduce investment, employment, and prices, and makes them less likely to invest in new technologies or open new facilities. This provides causal evidence for the uncertainty–investment channel, in contrast to earlier observational studies that relied on instrumental variable strategies. Their experimental approach complements the System-GMM identification strategy employed in Article I.

The evidence reviewed thus far shows that uncertainty causes firms to raise their investment trigger and retreat into inaction. An equally important question, however, is what reduces the option value of waiting and thereby restarts investment, as this has direct implications for both corporate strategy and public policy. Bloom, Bond, and Van Reenen (2007) provide the key theoretical and empirical answer using UK firm-level data. They show that the relationship between uncertainty and investment unfolds in two phases. First, there is a caution effect, in which rising uncertainty leads firms to pause investment as the option value of waiting increases. Second, there is a rebound effect, whereby the resolution of uncertainty – rather than a recovery in demand per se – releases pent-up investment as the trigger threshold falls.

This distinction is important. It implies that firms can restart investment even before expected profitability returns to pre-shock levels, provided uncertainty declines sufficiently. Bloom (2009), identifying uncertainty shocks through stock market jumps and the VIX[2] in a calibrated general equilibrium model, adds a further insight: the *speed* of uncertainty resolution determines the degree of scarring. Sharp, short-lived shocks cause less lasting investment damage than prolonged moderate uncertainty, as the option value collapses quickly and the rebound is rapid. By contrast, prolonged periods of moderate uncertainty – typical of slowly unwinding policy or financial crises – keep firms within the band of inaction for extended periods, leading to persistent investment weakness. This pattern is consistent with the prolonged investment slowdown observed in European manufacturing following the 2008–2009 and 2011–2012 crises. The policy implications of this dynamic are discussed in Section 4.1.

The role of credit constraints

The impact of irreversibility is not felt in isolation. Its effects are amplified through interactions with other real-world frictions, particularly financing constraints (the financial frictions channel) and imperfect market competition (the market power channel). The theoretical foundation for credit constraints in investment models is

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[2] CBOE volatility index that represents the market's expectation of 30-day forward-looking volatility derived from S&P 500 index options.

provided by Stiglitz and Weiss (1981), who show that information asymmetry between borrowers and lenders can lead to equilibrium credit rationing. In such settings, firms that can invest productively at the prevailing interest rate may still be denied credit – not because they lack creditworthiness, but because lenders cannot distinguish them from higher-risk borrowers.

The financial friction channel posits that increased uncertainty exacerbates this asymmetry: it raises a company's perceived default probability, leading to higher costs for external funds and tighter credit constraints precisely when investment opportunities may be most valuable.

Caggese (2007) develops a model where irreversibility and financing constraints mutually reinforce each other. During a downturn, a firm that is locked into excess fixed capital cannot easily downsize. If it is also financially constrained and needs to cut spending, the entire adjustment is forced onto its variable capital (e.g., inventories, materials), deepening losses and further tightening the constraint. For financially constrained firms, the risk of being locked into excess capital is particularly severe, as resulting losses erode internal funds and make future investment even less likely. The financing structure of investment further amplifies this mechanism, as shown by Baum, Caglayan, and Talavera (2008). Firms that fund fixed assets largely through debt face a more fragile position during downturns: assets are illiquid, while debt obligations remain fixed despite falling revenues. High leverage therefore increases the cost of being 'locked in', raising the ex-ante value of waiting.

Schauer (2019) provides empirical evidence that the financial frictions and irreversibility channels affect different types of assets in different ways. For capacity expansion investments (highly irreversible), the negative effect of uncertainty remains strong regardless of a company's financial status, indicating that the irreversibility channel dominates. For non-capacity investments (less irreversible), uncertainty has a negative effect only for financially constrained companies, where the financial friction channel is more relevant. This distinction helps explain why even relatively flexible investments may be curtailed in periods of heightened uncertainty.

Market structure provides an additional layer to this interaction. Theory suggests that the negative link between uncertainty and investment is stronger in imperfectly competitive markets. Guiso and Parigi (1999) test this by splitting firms based on company-level profit margins, used as a proxy for firm-level market power. They find that the negative effect of uncertainty is roughly twice as large for companies with substantial market power as for those operating in more competitive industries. This indicates that market structure is another critical factor that amplifies the deterrent effect of uncertainty on irreversible investment decisions.

An important extension concerns how uncertainty and credit constraints interact with investment across the business cycle. Periods of high aggregate uncertainty often coincide with tighter credit constraints, creating a double friction that should be especially damaging for irreversible investment. Using BEEPS survey data on manufacturing firms from ten Central and Eastern European (CEE) countries, Männasoo and Meriküll (2014) show that credit-constrained firms are significantly less likely to undertake R&D. After accounting for endogeneity, they find that R&D is countercyclical, consistent with the opportunity-cost argument of Aghion et al. (2010). In a follow-up study covering the Great Recession and recovery period, Männasoo and Meriküll (2020) also find that credit-constrained firms are approximately 32 percentage points less likely to engage in R&D. However, this effect is concentrated in boom periods, when demand for investment financing is high, rather than in recessions. This adds a cyclical dimension to the reinforcement mechanism described by Caggese (2007): while Article I of this thesis documents that irreversible fixed investment during downturns harms risk-adjusted performance, Männasoo and Meriküll's results suggest that credit constraints suppress long-term investment most forcefully during upswings. The welfare costs of financial frictions thus appear to be distributed asymmetrically across the cycle. Their CEE focus also highlights that the reinforcement mechanism may operate with particular intensity in catching-up economies with less developed financial and venture capital markets (Brown et al., 2011) – a source of heterogeneity within Article I's EU-wide panel.

A second amplifying friction is market power. Theory suggests that the negative link between uncertainty and investment is stronger in imperfectly competitive markets. As noted above, Guiso and Parigi (1999) find this effect to be roughly twice as large for firms with substantial market power. However, Ghosal and Loungani (2000) document the opposite pattern, showing the negative investment–uncertainty relationship to be stronger in more competitive industries. This discrepancy may reflect differences in how market power is measured (profit margins vs. concentration ratios) as well as differences in institutional settings. Article I contributes to this debate by controlling for industry density, which captures a different dimension of competitive structure from the profit margin proxy used by Guiso and Parigi (1999).

The evidence reviewed above shows that irreversibility transforms uncertainty into a clear deterrent to capital accumulation. This effect is amplified by financing constraints – whose impact varies over the economic cycle – and by market structure. Its impact on financial performance is also shaped by the macroeconomic environment, with periods of financial turmoil leading to extreme prudence and investment paralysis (Chen & Funke, 2010).

Post-crisis research has reinforced these mechanisms. Kolev and Randall (2024) report that firms facing high uncertainty experience a 3 percentage-point drop in investment rates, while Coad et al. (2023) find that R&D-intensive and small firms – those most exposed to irreversibility and financial constraints simultaneously – were disproportionately affected by pandemic-related uncertainty. Although the irreversibility and credit constraint mechanisms discussed above have been well established, one dimension that has received comparatively less attention is how companies' debt flows interact with investment type and cyclical conditions to shape financial performance. This concerns not only leverage levels but also the dynamics of borrowing and repayment alongside investment decisions. Kalemli-Özcan, Laeven, and Moreno (2022) take a step in this direction by showing that debt overhang reduced corporate investment during the European crisis through a channel independent of aggregate demand effects.

These contributions confirm that the investment–uncertainty nexus generalises across different types of aggregate shocks. However, despite this growing body of evidence, there remains a lack of large-sample micro evidence on how firms' investment decisions under uncertainty – while distinguishing between fixed and current investment – and concurrent changes in debt flows translate into risk-adjusted performance across the business cycle. In particular, prior work has not systematically documented whether non-linear thresholds in cyclical adversity – such as ranges of negative output gaps or elevated price volatility – exist beyond which irreversible investment becomes especially harmful for risk-adjusted ROA and ROIC. Article I addresses this performance-focused gap using an EU-wide panel of manufacturing companies.

1.2 Consumer choice: Expected utility and rationality

The standard framework for decision-making under uncertainty is Expected Utility Theory (EUT), formalised by von Neumann and Morgenstern (1944) and extended by Savage (1954/2012). While EUT applies to both companies and consumers, it is particularly foundational for modelling individual consumer choice, which is the focus of Articles II and III. EUT posits that rational agents choose among risky prospects by maximising the expected value of a utility function defined over outcomes. The theory rests on four central axioms that guarantee the existence of a well-behaved utility function (for a detailed discussion, see Briggs, 2023[3]).

Within the strict EUT framework, 'inertia' must be rationalised as a preference. If a consumer does not switch to a cheaper competitor providing the same service, the model infers that the consumer derives higher utility from the incumbent. This utility premium is often modelled as Risk Aversion, captured by the curvature of the utility function $U(w)$, where $U''(w) < 0$. A consumer may therefore prefer to stick with a known, slightly more expensive service (Brand A) over a new, cheaper alternative (Brand B) because the outcome of sticking with Brand A is certain (zero variance), whereas switching to Brand B carries performance risk. Specifically, the risk entailed in switching is the uncertainty about whether the service quality of the new provider will meet the consumer's needs – for example, whether future insurance claims will be handled satisfactorily.

However, while EUT can account for persistence through risk aversion, it struggles to explain inertia in settings where uncertainty is low or absent. It also performs poorly when the assumption of Independence of Irrelevant Alternatives (IIA) is violated (Matějka & McKay, 2015).

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[3] **Completeness:** For any two bundles or lotteries ***A*** and ***B***, the agent can strictly prefer ***A***, strictly prefer ***B***, or be indifferent. This ensures that agents are never paralysed by indecision

Transitivity: If $\boldsymbol{A} \succ \boldsymbol{B}$ and $\boldsymbol{B} \succ \boldsymbol{C}$, then $\boldsymbol{A} \succ \boldsymbol{C}$. This consistency is crucial for stable preferences over time.

Continuity: Preferences do not exhibit sudden jumps; if $\boldsymbol{A} \succ \boldsymbol{B} \succ \boldsymbol{C}$, there exists a probability *p* such that a lottery mixing ***A*** and ***C*** is equivalent to the certain outcome ***B***.

Independence: This is the most critical and controversial axiom regarding inertia. It states that if $\boldsymbol{A} \succ \boldsymbol{B}$, then a mixture of ***A*** with a third option ***C*** must be preferred to a mixture of ***B*** with ***C*** with the same probability. Formally, $p\boldsymbol{A} + (1-p)\boldsymbol{C} \succ p\boldsymbol{B} + (1-p)\boldsymbol{C}$.

The IIA assumption, embedded in standard discrete choice models such as the Multinomial Logit, implies that the relative probability of choosing between two options depends only on those options. In practice, however, this property is often violated. Empirical evidence shows that the introduction of a default option or changes in framing (salience) can significantly shift choice probabilities in ways not predicted by EUT. Simply designating an option as the 'status quo' increases its likelihood of being chosen, even if its intrinsic utility has not changed – a phenomenon known as status quo bias (Samuelson & Zeckhauser, 1988). Matějka and McKay (2015) show that rational inattention endogenously generates status quo bias.

This limitation becomes particularly clear in empirical settings, discussed later in Section 2.2.1, where the financial costs of inertia are too large to be explained by plausible levels of risk aversion. For example, consumers in health insurance markets often forgo substantial savings by remaining in strictly dominated plans (see Ho et al., 2017; Abaluck & Gruber, 2016). Such behaviour would imply implausibly high coefficients of absolute risk aversion under EUT (Handel, 2013).

1.2.1 Inertia in consumer choice: Bounded rationality and behavioural frictions

The persistence of consumer choice is a long-standing puzzle in economics. In a frictionless neoclassical world, a consumer's decision to repurchase a product or remain with a service provider is interpreted as a signal of revealed preference: the incumbent product maximises utility subject to budget constraints. Under this paradigm, 'inertia' is effectively non-existent; stability in choice reflects stability in preference or the continued superiority of the chosen good.

However, a vast body of empirical evidence contradicts this frictionless view. Consumers systematically leave money on the table. They remain in health insurance plans that are dominated financially and medically by available alternatives, fail to switch electricity providers despite deregulation designed to lower costs, and overlook cheaper financial products due to the cognitive costs of search and switching. This phenomenon, broadly termed 'consumer inertia', suggests that the stability of market shares of goods and services of different providers often reflects market friction rather than consumer satisfaction. Articles II and III of this thesis examine these mechanisms in the context of the Estonian car insurance market.

One way to rationalise this behaviour is to relax the assumptions of EUT. In its standard form, EUT assumes that agents evaluate all available alternatives and select the option that maximises expected utility across the entire choice set. Simon (1955, 1957) challenged this view, arguing that such assumptions are biologically and cognitively unrealistic, as individuals lack the capacity to process all available information, compute expected utilities for every state, and rank every alternative. Instead, agents 'satisfice' – that is, they search only until they identify an option that meets a specific aspiration level. Once this threshold is met, the search stops. In this bounded rationality framework, inertia is the natural state of a satisficer. If a current product remains affordable and functional, there is little incentive to incur the cognitive cost of searching for alternatives. The 'cost' of inertia is therefore not the financial loss of missing the best deal, but rather the preservation of limited cognitive resources (see Gigerenzer, 2020, for an overview of bounded rationality).

Notably, consumer research distinguishes this passive adherence from active loyalty. While both manifest as repeat purchasing, brand loyalty is driven by a favourable psychological evaluation of a brand's performance. In contrast, inertia – or state dependence – is characterised by a lack of active deliberation or information seeking prior to a subsequent choice (Maheswaran & Jacoby, 1990). As noted by Jacoby and Kyner (1973), inertial consumers may renew policies not because of deep-seated preference but to minimise cognitive effort and avoid the perceived costs of change. Empirical work supports this distinction (Dubé et al., 2010), typically grouping explanations for repeat behaviour into three categories: (1) preference-based loyalty, (2) learning about product quality, and (3) search costs and inattention.

These three categories carry distinct structural implications for identification. Preference-based loyalty represents true state dependence, i.e., genuine utility updating in favour of the incumbent. Learning effects represent rational Bayesian revision of quality beliefs. Inattention represents spurious state dependence as the consumer appears to prefer the incumbent only because no alternative was evaluated. All three produce identical patterns in reduced-form switching regressions, which is why estimates of 'brand loyalty' in studies that do not account for attention or search frictions are likely upward-biased (Handel, 2013). Articles II and III are designed to address this directly: Article II separates learning from preference using claim-type variation; Article III uses the two-stage attention-choice structure to separate spurious from genuine state dependence.

Inertia with bounded rationality: Search and switching costs

From a classical perspective, inertia is a rational response to market frictions. Stigler (1961) established that information acquisition requires resources – time, effort, and money – so rational individuals search only until the marginal benefit equals the marginal cost. These frictions are often divided into switching and search costs.

Even with full information (zero search costs), consumers may still exhibit inertia if switching providers is costly. Klemperer (1987) classifies these costs into transaction, learning, and contractual costs. A rational consumer switches only if the utility gain from an alternative exceeds the sum of these costs (Klemperer, 1995; Farrell & Klemperer, 2007). Burnham et al. (2003) further refine this typology into procedural (administrative burdens), financial (exit fees), and relational costs (loss of relationship with an agent).

Unlike switching costs, search costs are ex-ante frictions: the consumer does not know the price or quality of alternatives without paying a cost. Theoretical models like the Diamond Paradox (Diamond, 1971) illustrate that even small search frictions can lead to extreme inertia and monopolistic pricing.[4] To resolve this paradox, modern models incorporate heterogeneity in search costs or sequential search strategies, where consumers obtain quotes one at a time (Stahl, 1989).

[4] In a market with homogeneous goods, and if all consumers face a strictly positive search cost *s*, the following paradox occurs: (1) consumers will only search if they expect to find a price lower than the monopoly price by the amount of *s*; (2) knowing that consumers face a search cost, no firm has an incentive to undercut the monopoly price even by a small amount since doing so will not attract consumers who are not searching; (3) the unique equilibrium is for all firms to charge the monopoly price, and for no consumers to search; as a result, even small search frictions can lead to total market failure.

A further source of inertia arises in markets for 'experience goods', such as insurance, where quality is only revealed after consumption, e.g., after an insurance claim is filed (Nelson, 1970). For the consumer, insurance combines search, experience, and credence dimensions, implying that inertia cannot be attributed to a single mechanism. In the broker-mediated Estonian setting, monetary search costs are largely eliminated, as prices are observable at no cost through comparison platforms. At the same time, standardised risk profiles reduce adverse selection concerns on the insurer side. What remains is inertia driven by trust in the incumbent and by rational inattention, even when monetary search costs are close to zero.

Insurance is a particularly strong case of an experience good because its core service – claims handling – occurs infrequently and often only once or twice over the life of a policy. Its quality cannot be meaningfully assessed from websites, product leaflets, or price alone. As a result, accumulated trust in an incumbent insurer becomes a particularly durable switching barrier. Moreover, the informational signal from a claim event is unusually salient and asymmetric: a poor claims experience is both more surprising and more revealing than in markets where quality is more routinely observable. This creates an information asymmetry where the incumbent provider is often a known quantity, especially after having a claims experience with it, while competitors represent uncertainty. Consumer knowledge may accumulate as an intangible asset; switching would mean forfeiting the accumulated relational capital and re-entering a state of uncertainty about service quality (Schlesinger & Von Der Schulenburg, 1993). An analogous dynamic operates in financial markets, where retail investors exhibit persistent preferences for familiar stocks even after controlling for informational differences (Grinblatt & Keloharju, 2001) – a familiarity premium that narrows but does not disappear with experience.

Empirical literature on learning (Sargent, 1993; Evans et al., 2001) suggests that this dynamic creates a lock-in effect. Israel (2005) models this by estimating learning and lock-in using departure decisions, while recent studies have examined switching in the context of moral hazard (Liu et al., 2020) and bill-shock learning (Grubb & Osborne, 2015). In such settings, the anticipated psychological cost of leaving a trusted provider often outweighs the potential financial benefits of switching.

Empirical work has sought to disentangle learning effects from switching costs in repeated-choice settings. Osborne (2011) estimates both simultaneously for a frequently purchased packaged good and finds that omitting either leads to significant bias, with learning and switching costs reinforcing rather than substituting for each other. In a different context, Miravete and Palacios-Huerta (2014) analyse consumer behaviour in the U.S. local phone market, distinguishing endogenous learning from pure inertia and finding that consumers update their choices after negative experiences, helping them to make better decisions over time. Wu et al. (2024) extend this logic to information search, finding that consumers' prior beliefs about prices are often miscalibrated but adjust quickly with new observations – a finding that underscores the role of accumulated experience in reducing search frictions over time.

Rational and behavioural inattention

While the uncertainty discussed in Sections 1.1 and 1.1.1 relates to macroeconomic and demand uncertainty faced by companies, the rational inattention literature addresses a different but related form of uncertainty: decision-relevant uncertainty arising from the agent's incomplete knowledge of available options. A consumer who has not reviewed renewal offers, for example, does not know the current prices of alternative insurers. The uncertainty here is not about the state of the world, but about the structure of the choice set itself. While neoclassical models assume consumers maximise utility net of search costs, recent theories address the cognitive allocation of attention. Sims (2003) argues that, because attention is limited, it is often rational for consumers to ignore minor differences between alternatives. This gives rise to the theory of rational inattention (RI), where the value of revising prior beliefs is weighed against the cost of processing information.

Sims (2003, 2005) formalises this idea by modelling the economic agent as an information channel. In classical information theory, a channel (like a telephone wire) has a maximum capacity, denoted as κ (bits per second). If the incoming signal contains more information than κ, the receiver cannot reconstruct it perfectly, leading to errors (Sims, 2005). Sims applied this to economic agents that have a prior belief about the state of the world (e.g., in the context of this thesis, the prices and key non-price features of all insurers in the choice set). To make a better choice, they must process information to reduce the uncertainty of this prior.

A key contribution of this framework is that the information structure becomes endogenous. Agents are not simply passive recipients of noisy signals; they choose how precisely to process different types of information. They may allocate more attention to variables that have a large impact on utility and less to those that matter little (Hébert & Woodford, 2017). In the Estonian car insurance setting examined in Articles II and III, product features such as deductibles and coverage are largely standardised, so price becomes the primary dimension of uncertainty – although non-price attributes, such as brand and claims experience, are also incorporated into the analysis.

This framework also provides a resolution to the 'Inertia Puzzle' in macroeconomics and offers an alternative foundation to traditional sticky-price models (Maćkowiak & Wiederholt, 2009). The main difference between the sticky-price models and RI is that in sticky-price models, economic agents are passive victims of delayed information, whereas in RI, they optimally choose which signals to ignore, since selective inattention to macroeconomic signals is itself the rational response to costly information processing. In subsequent work, Maćkowiak and Wiederholt (2015) extended this logic to households.

Rational inattention provides a rigorous micro-foundation for inertia in several ways. Firstly, it generates an endogenous Status Quo Bias where economic agents optimally choose to be 'anchored' to their priors (past choices) because shifting the probability mass away from the prior requires costly information processing (Dean & Neligh, 2023). The higher the information cost, the stronger this anchoring effect.

Secondly, RI predicts that consumers may ignore small changes in value. A marginal price reduction by a competitor may not justify the cost of processing new information, so switching does not occur unless the price difference exceeds a certain threshold. This prediction is supported by experimental evidence (Caplin, Dean, and Martin, 2011).

Finally, RI provides a micro-foundation for the 'consideration set', which is the subset of options an economic agent actively evaluates. This concept plays a central role in the structural model applied in Article III and is discussed further in Section 2.2.3.

Experimental and empirical validation of rational inattention

Caplin and Dean (2015) derived necessary and sufficient conditions for testing whether observed choice data are consistent with any cost-of-information function, providing the first formal test of the RI premise that attention responds to incentives. In essence, agents allocate more attention to high-stakes decisions and less to routine or low-value ones, producing a systematic and predictable pattern of selective inattention across contexts.

This insight has been applied across a range of domains. In finance, for instance, Van Nieuwerburgh and Veldkamp (2010) applied RI to explain home bias in investment portfolios, and Mondria et al. (2013) extended this logic to explain financial contagion. Meanwhile, Cheremukhin et al. (2015) estimated information costs and found that deviations from rational behaviour arise from a deliberate disregard of information rather than from physical cognitive limits. In their experiments, most participants exhibit a linear marginal cost of information – leading to logit-like choice behaviour – rather than a fixed capacity limit. A dynamic extension of their model predicts that choices become more consistent over time as participants learn about the environment. Kacperczyk et al. (2016) further applied RI to mutual fund managers, finding that managers switch their attention allocation over the course of the business cycle.

In a related investment vein, Dzieliński, Rieger, and Talpsepp (2018) provide cross-sectional evidence that attention to stocks is not only limited but also asymmetric, increasing disproportionately after negative returns. Using analyst coverage as a proxy for the general level of attention, they show that firms attracting more attention also exhibit stronger volatility asymmetry and that this effect is most pronounced among stocks with low institutional ownership, where retail investors – who are more susceptible to attention-driven behaviour – dominate. This asymmetry resonates with the consumer insurance setting studied in Articles II and III, where negative events such as claims appear to trigger heightened attention and stronger switching responses.

Experimental work has further refined the RI framework. Dean and Neligh (2023), for example, designed experiments that differentiate between competing versions of RI. Their results confirm that individuals rationally adjust their attention in response to incentives, supporting the general RI model over simpler models of fixed error. At the same time, they find systematic deviations from the simple Shannon model: participants are less responsive to incentives than the model predicts and have greater difficulty distinguishing between perceptually similar (‘close’) states than between more distinct ones, even when payoffs are identical.

Mackowiak et al. (2023) review applications of RI across a wide range of economic fields. These include portfolio choice in finance (e.g. Van Nieuwerburgh & Veldkamp, 2010), attention discrimination in labour markets (Bartoš et al., 2016), political economy – particularly voter ignorance (Matějka & Tabellini, 2021) – and consumer choice (Matějka & McKay, 2015). More recently, Maćkowiak et al. (2025) extend this literature by analysing how RI shapes the transmission of ‘news shocks’ – that is, information about future productivity.

An important recent contribution comes from Brown and Jeon (2024), who develop and estimate a structural demand model grounded directly in the RI framework for Medicare Part D insurance choice. They show that individuals acquire more information when the stakes of an uninformed choice are higher, consistent with the RI prediction that attention is endogenous to incentives. Their model also demonstrates that reducing the number of available options can raise welfare not only through improved choice quality but also through savings in information processing costs. This result has direct implications for the broker-mediated setting studied in Articles II and III, where the standardised offer template of approximately five options may act as an attention-facilitating device that reduces processing costs relative to the full market of eleven providers.

In the context of an insurance renewal, this framework implies that consumers may rationally choose to remain inattentive to the fine print of competing offers – or even to their own renewal premium – if the expected gains from processing that information are too small to justify the cognitive effort required.

Behavioural economics and behavioural frictions

Another lens through which to explain inertia is behavioural economics. Separately from search cost and rational inattention models, the psychological biases literature shows that consumer choices are also shaped by cognitive heuristics and systematic errors that can reinforce inertial tendencies. DellaVigna (2009) provides a comprehensive overview of deviations from rationality, including nonstandard preferences and beliefs. Harrison (2025) argues that many apparent deviations from rationality in insurance markets can instead be attributed to heterogeneous beliefs, risk preferences, or time preferences rather than true irrationality.

Building on Simon's concept of bounded rationality, Kahneman and Tversky (1979, 1981) and others established that decision-making is influenced by recurring cognitive biases – such as anchoring, framing, and the availability heuristic – that systematically distort choices. These biases – such as the sunk cost fallacy and loss aversion – help explain why individuals fail to search optimally or persist with suboptimal options.

Gabaix (2019) surveys manifestations of behavioural inattention and methods for measuring attention empirically. One approach exploits violations of Slutsky symmetry – the prediction that cross-price demand responses should be symmetric if consumers fully optimise. In this framework, the effect of insurer A's price on demand for insurer B should equal the effect of B's price on demand for A. When this symmetry fails, it indicates that consumers do not attend equally to all options (Abaluck & Adams-Prassl, 2021). Synthesising evidence across studies, Gabaix (2019) suggests an average attention parameter of around 0.44, indicating that behaviour lies roughly midway between full rationality and complete inattention.

Recent work by Schneider and Sutter (2026) adds a complementary perspective. They show that the weak empirical link between risk preferences and actual behaviour observed in real world settings – particularly in insurance and financial settings – may arise because the wrong dimensions of preferences are being measured. Using incentivised experiments with 658 adolescents, they find that higher-order risk preferences, specifically prudence and temperance, predict health, financial, and prevention behaviour in domains where standard risk aversion yields null results. This implies that what may appear as inattention or irrational inertia could partly reflect unobserved precautionary motives. This distinction is relevant to the context of this thesis: the consumer inertia documented in Articles II and III operates in a setting where risk aversion alone would predict more switching than is observed, and unobserved heterogeneity in prudence could contribute to the residual inertia that Article III attributes to inattention.

While both rational inattention and behavioural inattention models emphasise how agents allocate limited cognitive resources, they differ in their underlying assumptions. Both predict that more important or volatile variables will receive more attention. However, the RI model treats the agent as solving an explicit information-processing problem, optimally allocating attention subject to constraints, while Gabaix's model adopts a more boundedly rational perspective, in which agents simplify the decision of what to attend to in the first place, thus avoiding the infinite-regress problem of optimising the optimisation process.

In essence, Gabaix's behavioural inattention provides a middle ground between bounded rationality and rational inattention. It is more structured and endogenous than the early heuristics-and-biases literature but more tractable and psychologically grounded in its assumptions than the more abstract rational inattention framework. The broader psychology-based literature on individual decision-making complements the rational inattention approach by highlighting additional behavioural mechanisms. While this literature offers valuable insights into decision processes, it is only partially incorporated in this thesis (primarily in Article II), and is therefore not reviewed in detail here.

Summary: Frictions in company decision-making and consumer choice

The theoretical discussion above establishes that both companies and consumers face specific frictions. For the companies, these fictions are investment irreversibility and credit constraints. For consumers, they are search costs and rational inattention. These frictions delay or distort adjustment to changing economic conditions.

On the company side, irreversibility is operationalised through fixed tangible investment, while flexibility is captured by current investment and working-capital flows. Financial frictions are proxied by debt flows and risk-adjusted performance measures akin to a z-score, constructed from ROA and ROIC scaled by the volatility of industry-level earnings. Uncertainty and cyclical conditions are measured using output gaps derived from detrended real gross value added and by excess producer-price volatility obtained from GARCH models.

On the consumer side, search and attention costs are captured through an unobserved attention stage, while switching costs and residual inertia are inferred from the probability of remaining with the incumbent conditional on paying attention. Learning is linked to claim-type variables (self-induced, third-party, and other claims) and their timing, and inertia is observed as repeated non-switching in the presence of fully standardised and transparent offer sets. The Estonian car insurance setting, with broker-generated offers from 11 insurers and almost no direct monetary switching costs, provides a quasi-experimental context in which these constructs can be empirically disentangled.

The thesis thus examines structurally analogous but contextually distinct frictions. For companies, the emphasis is on irreversibility and financial constraints shaping investment under cyclical adversity. For consumers, the focus is on search and attention frictions, switching costs, and learning from claims as drivers of inertia in repeated choices. The overarching aim is to improve empirical understanding of how such frictions shape outcomes – risk-adjusted company performance in EU manufacturing, and premiums and switching patterns in Estonian car insurance – under uncertainty.

The thesis does not attempt to build a single unified structural model that simultaneously explains company investment and consumer insurance decisions. Instead, it presents a parallel set of empirical essays under a shared conceptual framework of decisions under uncertainty with frictions. The analytical parallel is deliberate: both companies making irreversible investment decisions and consumers making repeated insurance choices face a common trade-off between acting now and waiting for better information. In the company context, this trade-off appears as the option value of waiting under investment irreversibility (Pindyck, 1991), and in consumer context, it is formalised as rational inattention (Sims, 2003).

The conceptual parallel runs deeper than analogy. Manufacturing companies hold a real option to delay capital commitment, i.e., options whose value rises with asset-specificity and macroeconomic volatility (Dixit & Pindyck, 1994; Abel et al., 1996). Similarly, consumers hold a real option to delay switching service providers, whose value rises with uncertainty about the new provider's quality and with the accumulated relational capital invested in the incumbent (Klemperer, 1995). In both cases, heightened uncertainty makes inaction a rational response. The welfare cost of this inaction – whether in the form of forgone investment returns or unrealised consumer savings – depends on both the duration of delay and the magnitude of underlying frictions.

This shared structure motivates the organisation of the thesis: Article I quantifies the performance cost of exercising irreversible investment options at the wrong moment in the business cycle, while Articles II and III decompose the forces that sustain consumer inertia (inattention, learning, and residual brand preference) in a setting specifically designed to identify each friction separately. The three articles are connected by this idea that both companies and households may rationally delay seemingly beneficial actions due to option values, information costs, or behavioural frictions.

2. Methodology, empirical evidence and research contribution

2.1. Empirical evidence on companies' investment frictions

A substantial empirical literature has examined the link between uncertainty and corporate investment, often using panel data or survey evidence to study how shocks to demand and volatility affect capital expenditures. Bernanke (1983) showed that when investment is partially irreversible, an increase in uncertainty can depress investment even without changes in expected demand, as companies value the option to wait for more information. Using company-level data, Aghion et al. (2010) documented that credit constraints and countercyclical risk premia amplify this mechanism, particularly for financially fragile companies – a pattern also captured by Männasoo and Meriküll (2020), as explained in Section 1.1.1. Complementing this, Schauer (2019) and Guiso and Parigi (1999) provided micro-level evidence that uncertainty depresses the most irreversible components of investment, especially capacity-expanding projects, while leaving more flexible categories relatively less affected.

Most of this empirical work treats investment volumes and composition as the primary outcomes of interest and focuses on how they co-move with uncertainty, financial frictions, and market power. Much less is known about how these investment decisions, together with debt dynamics, map into risk-adjusted measures of financial performance across the cycle and whether there are non-linear thresholds in macro adversity where the impact of irreversibility becomes particularly severe. Article I addresses this gap by linking fixed and current investment and debt flows to risk-adjusted ROA and ROIC in a large EU manufacturing panel with explicitly measured cyclical conditions.

More recent empirical work, particularly since 2020, has reinforced and extended these insights. Vardar and Cifter (2025) analyse the impact of economic policy uncertainty – measured using the EPU index of Baker et al. (2016), incorporating both domestic and global components – on company performance in the European textile and clothing industry. Using System GMM on a panel of 2,129 firms across 11 EU countries from 2013 to 2023, they find that both domestic and global uncertainty negatively affect firm performance, with evidence of a non-linear, U-shaped relationship for domestic uncertainty. Importantly, they show that working capital acts as a buffer against uncertainty, particularly in retail sectors. This finding aligns closely with the mechanism proposed by Caggese (2007) and which is central to Article I.

Working capital (current assets net of current liabilities) plays a dual role in this thesis. In the theoretical framework of Section 1.1, it is treated as a form of 'current investment', representing the more flexible counterpart to irreversible fixed investment. Here, in the context of resilience during downturns, it functions as a liquidity buffer that absorbs revenue shocks. These two roles are conceptually complementary: it is precisely because current assets are more liquid and reversible than fixed assets that they can serve as a buffer when fixed investment locks the company into an adverse position. In line with this interpretation, Yu and Jin (2024) find that economic policy uncertainty reduces the financial performance of Chinese energy-intensive firms, though the impact is mitigated for firms with high cash holdings and low debt ratios – a pattern consistent with the financial friction channel emphasised in this thesis.

At the methodological level, Kalemli-Özcan et al. (2022) employ Orbis firm-level data with bank-level matching to study the debt overhang channel during the European crisis – a period of extreme uncertainty about sovereign solvency and credit availability. They show that debt overhang suppresses investment independently of demand-side factors, indicating that uncertainty about future financing conditions, not just product demand, constrains capital formation. This finding reinforces the importance of the financial frictions channel that underpins the empirical strategy in Article I.

2.1.1. Article I: Methodology and contribution

Prior empirical work has explored how uncertainty and irreversibility affect investment decisions, often without explicit financial performance outcomes and mostly in single-country or survey contexts. Studies by Hartman (1972), Abel (1983), McDonald and Siegel (1986), Dixit and Pindyck (1994), Caggese (2007), Guiso and Parigi (1999), and Schauer (2019) have analysed how firms adjust their capital stock in response to shocks and how financial and market frictions shape these adjustments.

What remains largely missing is large-scale micro-level evidence on how different types of investment (fixed versus current), together with contemporaneous debt flows, interact with cyclical adversity to shape risk-adjusted firm-level performance across countries and industries. While macro-level studies have documented non-linear output losses following crises (Reinhart & Rogoff, 2009; Jordà, Schularick, & Taylor, 2013), systematic firm-level evidence on whether there are performance-relevant thresholds in output gaps or price volatility – beyond which the harm from irreversible investment becomes especially acute – remains sparse. Article I addresses this gap at the micro level by focusing specifically on risk-adjusted financial performance rather than investment volumes.

Specifically, Article I links fixed and current investment, along with debt flows, to risk-adjusted measures of ROA and ROIC under explicitly measured cyclical conditions in a large EU manufacturing panel. Risk adjustment is implemented by scaling firm-level returns by the standard deviation of industry-level earnings, producing a measure analogous to a Sharpe ratio or an insolvency-risk z-score. This ensures that firms operating in more volatile industries must achieve higher average returns to maintain comparable performance.

Methodologically, the study employs the System-Generalised Method of Moments (GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach is well suited to addressing endogeneity between investment, financing decisions, and performance outcomes, as well as controlling for unobserved heterogeneity and dynamic persistence. The empirical analysis is based on an extensive panel from the Orbis Europe database, covering 10,190 manufacturing firms across 24 EU member states over the period 2005–2018. A key contribution of Article I lies in its measurement of 'cyclical adversity' along two distinct dimensions. First, a real value-added gap – derived using a Hodrick–Prescott filter and defined as a deviation of more than 3% below trend – captures demand-side shortfalls. Second, excess producer-price volatility, estimated using GARCH models, captures uncertainty in input and output prices. These measures reflect different but complementary channels through which macroeconomic conditions affect investment decisions: output gaps reduce expected demand for new capital, while price volatility raises the option value of waiting by making future returns more uncertain.

This dual measurement allows the analysis to distinguish between demand-driven downturns and periods of heightened uncertainty. The dependent variables, ROA and ROIC, are risk-adjusted by dividing EBIT by the standard deviation of industry-level returns, a formulation similar to the insolvency-measuring z-score. The validity of the System-GMM estimates rests on two diagnostic conditions. First, the absence of second-order serial correlation in the residuals, tested via the Arellano-Bond AR(2) statistic, which cannot be rejected in the baseline specifications, confirming that the instrument set is not contaminated by autocorrelation. Second, the validity of the overidentifying restrictions, tested via the Hansen J-statistic, the p-values for which are comfortably above conventional thresholds in the preferred specifications. To guard against instrument proliferation, the instrument count is restricted by collapsing the instrument matrix and limiting lag depth, following the guidance of Roodman (2009).

The primary contribution of Kepp and Männasoo (2021) lies in their empirical validation of the investment irreversibility argument within a dynamic empirical framework that accounts for financing constraints and macroeconomic cyclical conditions. While classic works by Hartman (1972) and Abel (1983) suggest that uncertainty may increase investment under perfect competition, Article I aligns more closely with the models of McDonald and Siegel (1986) and Dixit and Pindyck (1994), which argue that the 'option to wait' becomes more valuable as uncertainty rises. The study does not estimate the option value of waiting directly – doing so would require a fully specified structural model – but instead identifies its observable implication: a negative interaction between irreversible investment and adverse macroeconomic conditions. This indicates that firms investing during downturns would have been better off delaying, consistent with a high option value of waiting.

In this framework, fixed tangible investment – machinery, equipment, and buildings – is treated as the irreversible component of capital formation. This is an assumption grounded in the characteristics of such assets: specialised manufacturing equipment typically has thin secondary markets, low resale values relative to installation cost, and long economic lives, all of which are empirical correlates of irreversibility documented in the literature (Dixit & Pindyck, 1994; Kim & Kung, 2017). While the study cannot directly measure the degree of irreversibility for each asset, the distinction between fixed and current investment provides a practical and empirically grounded proxy, consistent with Schauer (2019).

Relative to the existing literature on investment under uncertainty and irreversibility, Article I contributes in several ways:

- It provides EU-wide firm-level evidence that (irreversible) fixed investment under deep cyclical adversity can reduce risk-adjusted ROA and ROIC, thereby shifting the focus from investment volumes to performance outcomes.
- It documents non-linear thresholds in output gaps and producer-price volatility where the adverse impact of fixed investment on risk-adjusted returns becomes particularly pronounced.

- It shows that working capital – captured through current investment and liquidity in current assets – can act as a buffer that partly mitigates the negative performance effects of adverse macro conditions interacting with irreversibility[5].
- It demonstrates how debt flows and financial frictions interact with investment decisions to shape performance, highlighting a reinforcement mechanism between cyclical adversity, credit conditions, and irreversibility.

In contrast to Caggese (2007), Guiso and Parigi (1999), and Schauer (2019), Article I contributes by linking their insights on irreversibility and uncertainty to explicit risk-adjusted performance measures in a multi-country panel, rather than focusing solely on investment quantities or survey-based measures of investment behaviour. Article I also differs from Vardar and Cifter (2025) and Yu and Jin (2024) in that it explicitly models the interaction between investment type (fixed vs. current) and cyclical adversity as the driver of performance variation, rather than treating uncertainty as a direct predictor of firm performance. It further departs from Kalemli-Özcan et al. (2022) in focusing on the investment–performance outcome rather than the leverage–investment decision and in measuring cyclical conditions through both demand-side (output gap) and price-uncertainty (GARCH volatility) indicators rather than through sovereign-bank linkages. These distinctions preserve the novelty of Article I's contribution, even in light of the post-2020 expansion of the literature.

2.2. Empirical evidence on consumer inertia

There is substantial empirical evidence of inertia across a wide range of markets. In packaged goods, Dube et al. (2010) have developed a methodology to separate 'brand loyalty' (a positive preference) from 'inertia' (passive switching costs), a distinction now widely used in the consumer inertia literature. Applied to insurance contexts, their approach shows that a significant share of customer retention is not driven by superior service or genuine preference, but by the hassle and psychological costs of switching – often valued at around 15–20% of the product price.

Similar patterns emerge in other settings. In online retail markets, De los Santos et al. (2012) estimate search costs in online bookstores at approximately \$1.35, relative to average book prices of \$8–23. In retail banking, Tufano (2009) documents persistently low switching rates for current accounts despite meaningful differences in fees and service quality. Comparable inertia is observed in the mutual fund industry (Hortaçsu & Syverson, 2004) and in studies focusing explicitly on switching costs (Luco, 2019).

From a policy perspective, these magnitudes suggest that even modest reductions in search or switching costs can generate substantial consumer welfare gains. Regulatory interventions have taken several forms – mandatory price comparison tools (as in the UK energy market), portability requirements for phone numbers (in telecoms), and standardised product formats (as in the EU-wide Insurance Product Information Document (IPID) or broker-standardised insurance offers in Estonia) – all of which

[5] See Section 2.1 for a discussion of working capital's dual role as both a form of current investment and a liquidity buffer.

directly reduce search costs. The most effective interventions tend to target the dominant friction first by reducing search costs when consumers are inattentive (as highlighted in Article III) and reducing switching costs when consumers are informed but reluctant to act.

In deregulated utility markets, inertia remains pervasive. A large share of consumers stay with incumbent providers despite substantial potential savings (Hortaçsu & Puller, 2008; Giulietti et al., 2014; Hortaçsu et al., 2017). More broadly, the subscription economy – from streaming services to software – is built upon a business model that leverages inertia through automatic billing and low-salience monthly payments. Karle et al. (2025) provide an overview of online search experiments and validate that elicited and directly measured search costs are consistent. Their results show that even in highly transparent digital markets, consumers do not engage in the exhaustive price comparisons that standard models predict – intuitively, when billing is automatic and the service functions satisfactorily, the perceived cost of not searching is low, allowing providers to charge a premium to inert subscribers.

Recent work further highlights the importance of attention. Einav, Klopack, and Mahoney (2025) document substantial inertia in newspaper subscriptions and estimate an average attention parameter of 0.18 across ten subscription services, ranging from 0.04 to 0.50, and show that inattention can increase firm revenues by 14–200%. Notably, this estimate aligns closely with the 18.1% mean predicted attention probability in Article III of this thesis, despite the very different market context. This convergence lends external validity to the estimates obtained in the Estonian car insurance setting.

Across markets, not only search costs but also switching costs create incumbent advantages and reduce competition (Schlesinger & Schulenburg, 1991, 1993). These costs encompass procedural, financial, and relational components that collectively exceed satisfaction in predicting consumer retention (Burnham et al., 2003).

Insurance markets provide particularly rich evidence on the magnitude of these frictions. Brown and Goolsbee (2002) show that internet comparison websites – analogous to the broker-mediated setting in this thesis, though in a different market – reduced term life insurance premiums by 8–15% by eliminating search frictions. Applied to auto insurance, their findings suggests that the 'cost' of not searching is a premium that is significantly higher than it would be in a more transparent market.

In the U.S. Medigap market, Lin and Wildenbeest (2020) estimate median search costs of $22 (based on 2009 data), with their elimination predicted to reduce prices by around 5% and increase consumer welfare by up to $321 (Lin & Wildenbeest, 2013) or $536 (Ho et al., 2017). More broadly, the U.S. health insurance market exhibits substantial switching costs, with adverse selection further complicating welfare implications (Handel et al., 2011). Evidence from European health insurance markets points in the same direction. Switching costs significantly shape consumer behaviour, particularly among older and less healthy individuals, who are less likely to switch providers (Boonen et al., 2015; Duijmelinck et al., 2015). Similar patterns are observed in Germany, where reforms to private health insurance markets have been used to identify switching frictions (Atal et al., 2019, 2025).

Drake, Ryan, and Dowd (2022) examine the sources of inertia in California's Health Insurance Marketplace by decomposing it into inattention, hassle costs, and preferences for provider continuity using a two-stage framework. They find that eliminating inattention and hassle costs would reduce repeated plan choice by 53 percentage points and that these two frictions act as complements rather than substitutes. The estimated welfare cost of inattention and hassle costs exceeds $1,790 per household per year, which provides a useful benchmark against which to compare the attention estimates from Articles II and III, where the welfare cost of inattention is smaller (approximately €25 per year in foregone savings) but the attention mechanism operates similarly.

In the car insurance market, Berger et al. (1989) provide one of the earliest empirical attempts to measure switching costs, defining them as the price difference required to induce consumers to switch away from their incumbent insurer. Schlesinger and Schulenburg (1991) extend this argument in the German insurance market in the presence of product heterogeneity and insurer pricing actions. In a subsequent study (1993), they use German survey data and a simple probit model to estimate search and switching costs as determinants of the switching decision. They construct an 'information index' based on respondents' perceived price rankings relative to actual prices, which serves as a proxy for search costs.

Closer to the setting of this thesis, Honka (2014) estimates that the total search costs for a typical U.S. auto insurance consumer amount to approximately $250. To contextualise this figure: the average annual auto insurance premium in the U.S. at that time was approximately $800–$900, implying that search costs represented roughly 25–30% of the annual premium – a sufficiently large fraction to rationally deter search even when meaningful price differences between providers exist. Honka further decomposes search costs into components, including the cost of becoming aware of an additional insurer (around $60) and the cost of obtaining a quote from a known insurer (around $35). Overall, estimated search costs range from $35 to $170, while average switching costs are about $40. Counterfactual analysis shows that eliminating search costs would increase switching to 60.4%, eliminating switching costs to 30.6%, and eliminating both to 61.9%, highlighting the dominant role of search frictions.

For comparison, Ericson and Starc (2012) find that only around 20% of consumers choose the cheapest plan on the Massachusetts Health Insurance Connector, a standardised exchange with visible pricing. The much higher share of price-optimal choices in Estonia (approximately 70% conditional on attention) reflects the additional salience created by the broker's comparison table and the near-complete product standardisation, which together strip away the product differentiation that sustains rational brand heterogeneity in other settings.

Kiss (2019), investigating the switching of motor third-party liability insurance providers in Hungary, used a two-stage model and a natural experiment – a government-run campaign – that provided exogenous variation for identification. He estimates combined search and switching costs in the range of €60 to €110 per policy and reconstructs individual choice sets using general pricing schedules.

Table 1 below summarises some of the studies that quantify search and switching costs using insurance market data. Across these studies, several patterns emerge. First, search costs tend to dominate switching costs as the primary friction: when consumers do not gather competing quotes, even eliminating switching costs has little effect on switching rates. Second, the magnitude of estimated frictions varies substantially by market and method ranging from tens to hundreds of euros or dollars per year but consistently exceeds consumers' apparent willingness to actively engage with alternatives. Third, in settings where search costs are dramatically reduced (such as broker-mediated or internet-facilitated markets), inertia persists, pointing to behavioural factors that include inattention and status quo bias as complementary drivers beyond purely monetary frictions. This pattern motivates the two-stage attention-and-choice framework used in Article III.

When estimating both components of inertia, product intangibility plays a critical role. In insurance markets, a key empirical trigger for switching is often a negative claims experience. Such events reveal poor service quality, eroding trust in the incumbent provider and weakening the trust-based component of switching costs, thereby prompting active search. This mechanism has been documented by Cohen (2005), who analyses it through the lens of asymmetric information, and by Israel (2005), who studies customer departures after a claim and finds that it indicates learning.

A primary consequence of inertia is the 'loyalty penalty', a form of price discrimination also known as price walking. Insurers, recognising the high inertia among existing customers, frequently apply incremental price increases at renewal, while offering competitive introductory rates to attract new, non-inert customers. A landmark study by the UK's Financial Conduct Authority (FCA, 2020) found that loyal customers were paying significantly more than new customers with identical risk profiles, concluding that the market was not working well for consumers.

Regulatory responses to this have varied across markets. The UK's Financial Conduct Authority (FCA, 2021) implemented rules banning price walking in home and motor insurance, requiring that renewing customers be offered prices no worse than those offered to equivalent new customers. This represents a direct intervention in the pricing mechanism to protect inert consumers. More targeted alternatives include mandatory disclosure of the previous year's premium alongside the renewal quote (a practice also required by the FCA), which dramatically lowers the cognitive cost of identifying a price increase without restricting insurer pricing freedom. A similar approach has been adopted in Estonia since 2025 for compulsory motor third-party liability insurance, where automatically renewed policies must make the previous premium salient.

The prevalence of inertia also dampens price competition. If a significant portion of a company's customer base is unlikely to switch, there is less incentive to offer competitive pricing to existing policyholders. At the same time, the complexity of insurance products increases the cognitive cost of comparison, reinforcing rational inattention (Johnson et al., 1993). While Articles II and III focus primarily on price as the observable driver of switching – partly reflecting the broker setting, which standardises most non-price product attributes – non-price competition remains relevant. Factors such as brand, claims-handling reputation, and service quality continue to influence behaviour. Article II shows that brand effects are statistically significant even after controlling for price, while Article III confirms a modest brand preference in the choice stage conditional on attention. These results suggest that while price is the dominant decision criterion when consumers actively compare options, non-price dimensions like brand, claims-handling reputation, and service quality sustain loyalty even when cheaper alternatives are available.

Table 1. Selective overview of search and switching cost studies

Study	Insurance type	Search cost magnitude / Welfare loss	Switching cost findings	Method	Study context
Abaluck & Adams-Prassl (2021)	General / Health	Significant consideration frictions (consumers ignore most options)	Not separately estimated (focus on identifying consideration sets)	Structural model (identified via asymmetric cross-price responses)	UK / US (methodological application)
Abaluck & Gruber (2016)	Health (Medicare Part D)	~$300–$373 (annual 'foregone savings' due to inconsistent choices)	Inertia increases over time (little evidence of learning)	Structural model (choice inconsistency framework)	United States, 2006–2009
Boonen et al. (2016)	Health	High impact of search (search behaviour strongly increases price sensitivity)	Psychological and transaction costs (reported by ~15% of non-switchers)	Survey + logit model (panel data analysis)	Netherlands, 2006–2012
Handel & Kolstad (2015)	Health (Employer-sponsored)	~$1,787 (mean impact of information frictions on WTP)	Not separately estimated (modelled as 'information friction')	Structural model + survey (linked to proprietary claims data)	United States, large firm
Heiss et al. (2021)	Health (Medicare Part D)	Dominant Factor (~50% of consumers are completely inattentive)	Significant (but secondary to inattention)	Structural model (two-stage: attention vs. choice)	United States, 2007–2010
Ho et al. (2017)	Health (Medicare Part D)	~$536 per consumer (potential savings if inattention removed)	High (insurers price based on inertia)	Structural model (demand + supply-side pricing response)	United States, 2006–2010
Honka (2014)	Car insurance	$35–$170 (internet: ~$35; offline: $100–$150)	~$40 (average)	Structural model (demand estimation)	United States, 2006–2007
Kiss (2019)	Car insurance	$60–110 per policy	~$60–$110 (estimated as total friction)	Natural experiment (regulatory advertising campaign)	Hungary
Lin & Wildenbeest (2020)	Health (Medigap)	Median $30	Not separately estimated	Structural model	United States, 2009
Maestas et al. (2009a)	Health (Medigap)	Average $72	Not separately estimated	Structural model	United States, 2004
Atal et al. (2019)	Health insurance	No direct quantification	Significant 'lock-in', switch rates doubled from 6.5% to 13% after the reform considered	Structural model	Germany, 2005–2011

Study	Insurance type	Search cost magnitude / Welfare loss	Switching cost findings	Method	Study context
Maestas et al. (2009b)	Health (Medigap)	Average $249	Not separately estimated	Structural model	United States, after 1992
Pauly et al. (2006)	Health (individual)	No direct quantification	Positive correlation with age	Reduced form	United States
Bolhaar et al. (2010)	Health	-	Likely higher for high-risk individuals	Survey analysis	Netherlands, 2006
Brown & Jeon (2024)	Health (Medicare Part D)	High (implied)	Not separately estimated	Structural model	United States, 2010–2015
Rowell & Zweifel (2024)	Car insurance	No direct quantification	Positive correlation with risk	Structural equation modeling	Australia, 1999
Hortaçsu et al. (2017)	Residential electricity	Dominant factor (~$222/year foregone savings)	Low / Minimal (<10% of inertia)	Structural model (search vs switching decomposition)	Texas (USA), 2002–2006

2.2.1. Research context: Estonian car insurance market

Articles II and III draw on data from the Estonian car insurance market. This setting has several distinctive features that contribute directly to the thesis's aims and novelty, most notably the quasi-experimental nature of the data-generating process. It is therefore useful to outline the broader development of the Estonian insurance market and relate it to the data used in these articles through a set of stylised facts.

Before turning to Estonia specifically, it is worth noting the structural features that make insurance markets particularly well suited for studying consumer inertia. These features motivate the research design choices in Articles II and III and place them within a broader industrial organisation literature. Insurance markets are characterised by two canonical information asymmetries that operate simultaneously but in opposite directions. The first is adverse selection, which is where consumers possess better information about their own risk type than insurers at the point of contracting, which can lead to risk segmentation and underprovision of insurance for high-risk individuals (Akerlof, 1970; Rothschild & Stiglitz, 1976). The second is moral hazard, which is where, once insured, the consumer has a reduced incentive to avoid the insured event, creating a post-contractual information asymmetry running in the opposite direction (Shavell, 1979; Arrow, 1963).

Both asymmetries have been extensively studied in motor insurance. Cohen and Einav (2007) use a large Israeli auto insurer dataset to show that risk type and risk aversion are positively correlated, implying that standard adverse selection models are incomplete without accounting for preference heterogeneity. In contrast, Chiappori and Salanié (2000) find only weak evidence of adverse selection in French automobile insurance once observable risk characteristics are controlled for, suggesting that residual asymmetries may be limited in well-functioning markets with detailed risk classification.

This point is particularly relevant for Articles II and III, as in the Estonian broker-mediated leasing setting, where the insurer receives a standardised risk profile for each vehicle and lessee (compiled by the broker and the leasing company), which substantially reduces the adverse selection problem relative to direct sales channels where the insurer must rely on self-reported information. The implication is that price variation across insurers in the comparison table reflects genuine pricing strategy and efficiency differences rather than risk segmentation, which strengthens the identifying assumption that the cheapest available offer is a welfare-improving alternative for the inert consumer.

The Estonian insurance market developed rapidly following the country's independence in 1991. Privately owned insurers emerged in the early 1990s, and – as in many post-transition economies – consumer demand was initially concentrated in non-life insurance rather than life and savings products. Evidence from other post-communist European countries (Born & Bujakowski, 2022) shows a similar pattern. This reflects the macroeconomic conditions of the time: high inflation reduced the attractiveness of long-term savings products, while the need to insure tangible assets such as vehicles and property drove demand for short-term, indemnity-based coverage.

From the outset, the market was dominated by non-life insurance, particularly motor lines. Motor Third Party Liability insurance became compulsory in Estonia in 1992, in line with later EU-wide requirements, and Motor Own Damage (Casco) insurance also became a central product. Over time, non-motor segments within non-life insurance have expanded, gradually reducing the relative importance of motor insurance, although motor lines continue to grow in absolute terms.

However, following a period of rapid growth, the market suffered a severe decline during the Global Financial Crisis. In the post-crisis period – covering the data used in Articles II and III – the market has grown steadily, with several structural shifts illustrated in Figure 2. While life insurance has remained a relatively small and declining share of the total market, the composition of non-life insurance has evolved: the share of motor insurance has gradually declined in relative terms, even as its absolute volume has continued to increase.

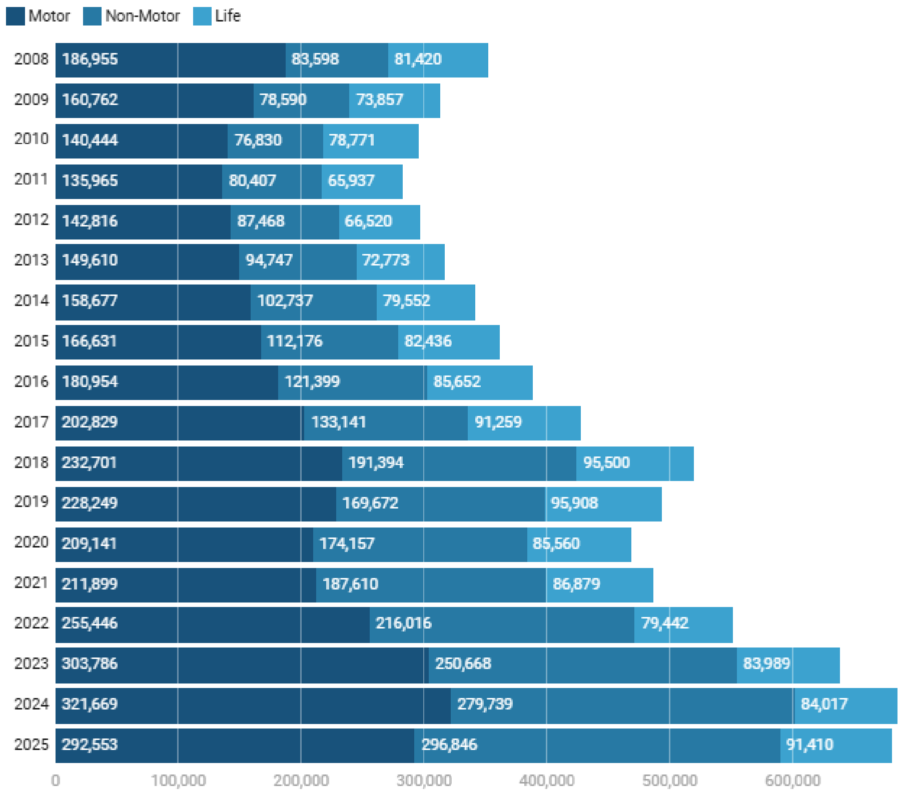

Figure 2 . Gross written premiums in the Estonian insurance market by lines of business, in €1000, 2008–2025. Data source: Statistics Estonia. Compiled by the author.

Taking a closer look at the motor insurance market, its development closely mirrors the evolution of leasing volumes. Figure 3 presents written premiums in motor insurance alongside both the total stock of lease exposure and the new lease exposure generated in each year (in €1,000). In Estonia, financial leasing has become the dominant form of new car financing. Approximately 80% of new private cars sold in Estonia are acquired through lease arrangements (Jõeveer & Kepp, 2023), making it the most common financing mechanism for new vehicles. Used car purchases, by contrast, are more frequently financed through personal savings or consumer loans. This structure contrasts with the broader European market average, where vehicle leasing historically accounts for roughly a third of new registrations, with traditional unsecured auto loans retaining a much larger share of the consumer auto finance mix (Leaseurope, 2023). Figure 3 visually highlights the seeming interdependence of the motor insurance and lease volumes.

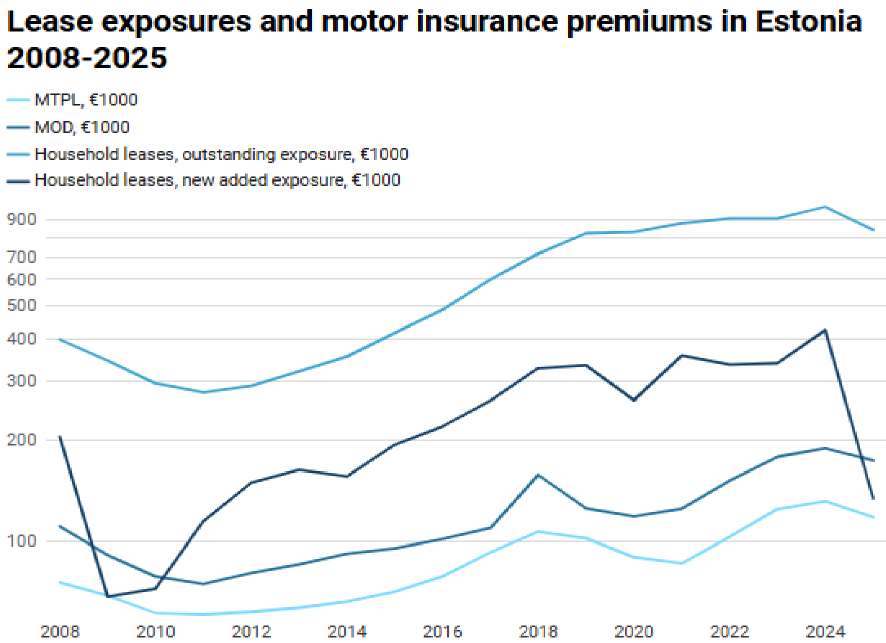

Figure 3. Lease exposures and motor insurance premiums in Estonia, 2008–2025 (logarithmic scale). Data source: Statistics Estonia, Bank of Estonia. Compiled by the author.

The car insurance market is also characterised by strong competition among providers. Figure 4 presents the market shares of all insurance companies offering Motor Own Damage and Motor Third Party Liability insurance over the period 2008–2025.

New entrants (such as Compensa Vienna Insurance Group in 2016 and LHV Kindlustus in 2021), portfolio acquisitions (e.g. RSA Insurance Group's takeover by PZU Group in 2014), and exits (such as QBE Insurance Group in 2012) illustrate that, despite its small size, the Estonian motor insurance market has remained competitively active. Thus, at any point in time, consumers face a relatively large set of competing insurers.

In both Articles II and III, the data are generated within a broker-mediated distribution system for leased vehicles. Prior to 2010, some leasing companies organised tenders to appoint a broker responsible for assembling a panel of insurance offers, while others adopted a sole-supplier model in which customers received a single pre-selected insurer's offer. The empirical analysis in this thesis focuses on the former arrangement. The data are obtained from a large broker serving multiple leasing companies and collecting standardised offers from 11 insurers. This tripartite system – leasing companies, broker, and insurers – is designed to ensure that all leased vehicles are insured from contract inception and that policies are concluded on market-consistent terms.

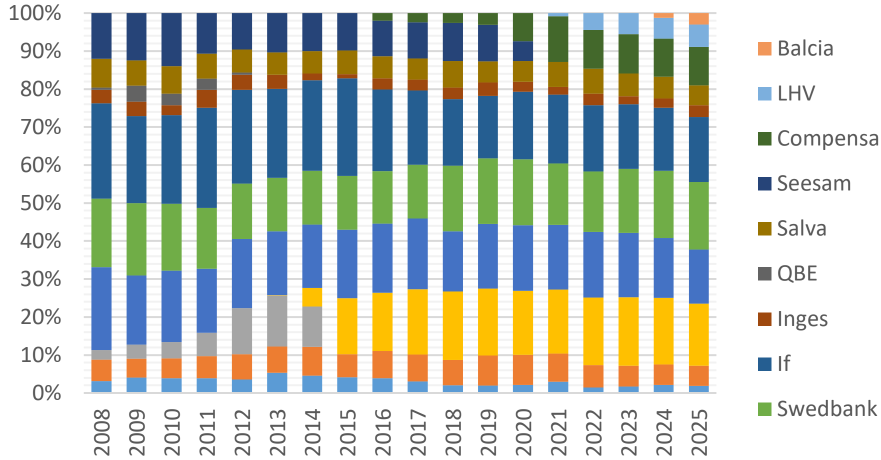

Figure 4. Motor insurance market shares in Estonia, 2008–2025. Source: Statistics Estonia, compiled by the author

The unit of observation in both articles is a consumer-year renewal event – in other words, each row in the dataset corresponds to a single consumer at a single renewal point and contains: (i) the full set of price offers received from all participating insurers, (ii) the consumer's choice of insurer, (iii) policy characteristics, and (iv) any claims information from the preceding policy period. Article III additionally incorporates new policy purchases. This structure allows the researcher to simultaneously observe what was offered, what was chosen, and what was experienced – without imputing any of these critical inputs.

The data generation process is as follows. The broker sends over a standardised set of consumer and car characteristics to the insurers, and they independently generate offers in real time. After receiving the quotes, the broker combines them into a comparison table sorted by price and deductible levels (mainly standardised around €200 or €300). The consumers are then able to observe these offers in a unified, non-branded presentation at no extra cost.

An additional feature of the data generation mechanism is that leasing companies require all participating insurers in the panel not to offer lower prices for the same leasing-bound risks through other sales channels. Hence, the pricing for the consumer choice set is representative of all offers presented to the consumer by the same insurers. The broker-mediated structure of this market has consequences that extend beyond data convenience. In standard insurance markets, the distribution channel determines who bears the information asymmetry and in which direction. In a direct sales model, each insurer observes only its own portfolio and cannot see competitors' offers to the same consumer, while the consumer must invest search costs to obtain comparable quotes. The broker model fundamentally restructures this arrangement: the broker acts as an information hub that simultaneously observes the consumer’s risk profile and all insurers’ pricing responses, enabling comparison that the consumer could not costlessly assemble independently. This intermediary role has been theorised as a partial solution to adverse selection whereby brokers can match consumers to appropriate risk categories more accurately than direct-sales channels because they have both the risk information and the market-wide pricing to identify optimal fits (Cummins & Doherty, 2006; Eckardt & Räthke-Döppner, 2010). For the empirical design of Articles II and III, this has a specific implication: adverse selection is substantially mitigated as an identification threat because the broker transmits a standardised risk profile to all 11 insurers simultaneously, meaning that price differences across offers reflect insurer efficiency and strategy rather than differences in risk classification.

The broker's role also introduces a trust dimension that is distinct from, but interacts with, the information asymmetry literature. In a direct sales relationship, the consumer's trust is placed in the insurer and accumulates through claims experience and repeated interaction. In the broker-mediated setting, trust is effectively bifurcated: the consumer must trust both the insurer to handle claims fairly and the broker to act in the consumer's interest when selecting and presenting the choice set. Broker trust therefore has a dual structure that does not map straightforwardly onto standard switching cost models.

Eckardt and Räthke-Döppner (2010), studying German insurance intermediaries, show empirically that consumers assign significant value to the perceived impartiality of the broker. They must believe that the broker is not steering them toward a preferred insurer. This perceived impartiality is conceptually distinct from trust in product quality. In the Estonian leasing-broker setting, the broker's impartiality is structurally guaranteed by the leasing companies' contractual requirements that all 11 participating insurers submit independent, non-discounted offers – a feature that removes the conflict of interest inherent in commission-driven brokerage (Cummins & Doherty, 2006). This structural impartiality has a direct implication for interpreting the inertia findings of Articles II and III: consumer inertia in this setting cannot plausibly be attributed to distrust in the comparison mechanism itself, as may be the case in commission-driven broker or price comparison website environments (Honka et al., 2017). Thus, any residual inertia after controlling for price differentials must reflect genuine preference components – such as brand trust, accumulated claims-handling experience, or rational inattention – rather than scepticism about the broker’s recommendations. This makes the Estonian setting unusually well suited for decomposing the sources of insurance inertia – an empirical clarity that constitutes an important part of the thesis contribution.

All data used in the articles consist of received offers, consumer choices with policy data, and subsequent claims data on these policies. In addition, the dataset is enriched by various external sources. The two articles differ in their time horizons, included covariates, and empirical designs, reflecting their distinct research questions and methodological approaches.

2.2.2. Article II: Methodology and contribution

Article II identifies the triggers of switching by examining claim-type learning, service experience effects, and consumer characteristics. It sits at the intersection of empirical work on insurance switching, search and switching costs, and learning from claims.

The prior literature has documented substantial search and switching frictions in car insurance and related markets. For example, Honka (2014) and Kiss (2019) use structural and two-stage models to study U.S. and Hungarian car insurance, respectively, but typically lack fully observed choice sets and rely on survey-based or imputed information on offers and awareness, with non-standardised products (in Honka, 2014) and non-trivial search and switching costs (Kiss, 2019). Moreover, Israel (2005), Miravete and Palacios-Huerta (2014), and others study learning and departures following claims but have limited information on claim types and often observe only one insurer's portfolio.

Consequently, an important gap remains: high-quality micro evidence on triggers of switching – especially claim-type-specific learning – in a setting where repeated choice sets are fully observed, products are standardised, renewal timing is exogenous, and monetary switching costs are minimal. Article II addresses this gap by exploiting Estonian Motor Own Damage (MOD, also known as fully comprehensive or 'casco') insurance broker data, in which all offers from 11 insurers, actual choices, and detailed claim classifications are observed over multiple renewal periods.

Measuring inertia involves solving an identification problem in econometrics: distinguishing the effect of past choices (state dependence) from the confounding influence of unobserved characteristics (heterogeneity). The most widely used framework for testing inertia is a dynamic binary response model in which the outcome is whether consumer *i* switches at time *t*, which is modelled as a function of individual characteristics, past choice, and unobserved heterogeneity.

Across the full panel, the average probability of a consumer switching insurer at any given renewal is approximately 11% – a low rate despite near-zero monetary search and switching costs and one that motivates the subsequent analysis of its behavioural and learning-based drivers.

The panel of choices presented to the customer includes the vast majority of options available in the market. The potential outside option beyond this consideration set is therefore unlikely to be better in its cover or premiums than the policies in the choice set. The timing of choices is exogenous, so there is no need to address endogeneity in decision timing. The intertemporal dimension is captured through lagged choice outcomes (such as price difference against prior year of the incumbent insurer) and claim histories as covariates. Given the data setting, Article II adopts a simplified logistic approach that follows both Boonen (2016) and Kiss (2019).

Switching behaviour is explained using covariates divided into direct monetary utility effects, brand loyalty and reputation effects, and learning effects. All variables – namely, the choices offered, choices made, consumer characteristics, and claims – are observed rather than imputed and are considered jointly within the context of inter-temporal decision-making. Thus, each renewal choice is understood as one episode in a repeated sequence of decisions in which past experience informs current behaviour.

It should be noted that Article II does not explicitly model the formation of the consideration set – that is, it does not attempt to identify which insurers a consumer was aware of or actively considered prior to making their choice. The data setting, in which a broker provides standardised offers from all participating insurers, largely removes this concern, since the full offer set is observed. However, any additional search for outside offers beyond the broker panel is not captured. This limitation motivates the structural attention decomposition in Article III, which explicitly models the prior stage of whether a consumer attends to the renewal offer at all.

Contribution of Article II

First, it studies switching behaviour within a single category of goods using a large panel of repeated, fully observed choice sets (and, to a large extent, entire consideration sets), including prices offered, contracts chosen, and claims incurred across a substantial share of the car insurance market. This contrasts with much of the earlier literature, where data are drawn from a single service provider (Israel, 2005) or where key inputs – such as prices and choice sets – must be imputed via questionnaires (Honka, 2014) or standard price lists (Kiss, 2019).

Second, the study exploits detailed claim information to explore how different types of claims – self-induced, third-party, and other – relate to subsequent switching behaviour, after controlling for price and other covariates. This enables the article to document asymmetric responses that are consistent with learning from service experience and with psychological mechanisms (such as dissatisfaction or gratitude) that may influence switching decisions.

Relative to Honka (2014) and Kiss (2019), Article II contributes by analysing a setting with fully standardised products, complete observed offers from multiple insurers, and negligible direct monetary switching costs. In such an environment, attention, learning, and non-pecuniary frictions play a central role. Relative to Israel (2005) and similar work on departures after claims, Article II contributes by distinguishing between claim types and linking them systematically to switching probabilities in a multi-insurer, repeated-choice setting.

The interpretations in terms of psychological mechanisms such as 'gratitude' towards an insurer after self-induced claims or 'hassle' after third-party claims are presented as hypotheses consistent with the observed asymmetric patterns, rather than as structurally identified channels. These mechanisms are not directly tested in Article II and remain to be examined in research settings specifically designed to identify them.

2.2.3 Article III: Methodology and contribution

Article III builds on recent structural and semi-structural work that seeks to separate attention and choice frictions in markets with repeated decisions, such as electricity, health insurance, and telecoms. Studies by Hortaçsu et al. (2017), Ho et al. (2017), Heiss et al. (2021), and Abaluck and Adams-Prassl (2021) develop models in which consumers first decide whether to pay attention to alternative options and then choose among them, but they typically face important identification challenges. In particular, consideration sets and search processes are often unobserved, offers are only partially observed or must be imputed, and monetary switching costs are non-trivial.

As a result, existing applications struggle to disentangle attention from choice when the underlying choice sets, search costs, and switching costs cannot be directly measured. What is largely missing is a setting in which the menu of offers, the relevant consideration sets, and monetary switching costs are almost fully observed, allowing a clean separation of attention and choice frictions within a two-stage framework. Article III fills this gap by exploiting quasi-experimental Estonian leasing-broker data, where offers are broker-generated and standardised, choice sets are fully observed, and monetary switching costs for consumers are negligible.

While Article II uses a reduced-form approach to document switching triggers and asymmetric learning effects across claim types, Article III adopts a structural approach to decompose consumer inertia into its attention and choice components. In this sense, the two articles are complementary: Article II focuses on the determinants of switching and learning effects, whereas Article III focuses on inattention and provides a structural identification of the underlying frictions. It builds on earlier methodological advances to identify inattention as a form of search cost, separately from other sources of inertia.

A key methodological issue in this literature concerns whether consumers search simultaneously or sequentially. One stream, originating in the 1990s, models search as sequential (e.g. Hauser and Wernefelt, 1990), where consumers consider a limited number of brands – typically three to five – and evaluate them one by one, deciding after each step whether to stop searching and purchase or to continue. In this framework, marketing activity primarily affects which products enter the consideration set rather than underlying preferences.

The alternative stream models search as simultaneous, where consumers decide on a fixed set of products to investigate *before* starting the search process and then commit to evaluating all of them jointly, as in Roberts and Lattin (1991). In their model, consumers consider a brand as long as its utility is above an individual-specific threshold. Meanwhile, De los Santos et al. (2012), using web browsing data, show that consumers' decisions to continue searching do not depend on previously observed prices, which contradicts the predictions of sequential search. Similarly, Honka and Chintagunta (2017) demonstrate that the nature of the search process can be inferred from the price distribution within observed consideration sets: sequential search tends to generate a disproportionately high share of low prices, a pattern not consistent with simultaneous search.

Honka et al. (2019) provide a comprehensive overview of the economic and marketing literature on consumer search and consideration sets. The central theme is that consumers have incomplete information and incur search costs to learn about prices and product attributes. Seminal works by Hortaçsu and Syverson (2004) and Hong and Shum (2006) first developed methods to infer search cost distributions from observed prices and market shares. A key empirical challenge, however, is disentangling search cost from switching cost when both are present. Wilson (2012) provides a theoretical basis for identification based on the shape of the demand curve and illustrates an empirical methodology for estimating separate measures of both costs, highlighting the bias that can arise if only one cost is considered.

Honka (2014) addresses this issue using a unique dataset that includes observations of consideration sets, obtained from survey responses to the question 'Which companies did you obtain quotes from?' This allows the search process to be directly inferred. If a consumer considers only their incumbent insurer, search costs must be the binding constraint; however, if a consumer gathers multiple quotes but remains with a more expensive incumbent, switching costs (or unobserved preferences) must explain the outcome. By modelling the decision process in steps (Decision to Search → Formation of Consideration Set → Final Choice), Honka structurally separates the parameters. She estimates search costs in US auto insurance at \$45 (online) to \$110 (offline), distinct from a switching cost of roughly \$40. This separation is crucial for policy, as reducing switching costs has little effect if consumers do not search in the first place.

Before discussing the methodology of Article III, it is important to note that the most direct identification of frictions comes from randomised controlled trials that exogenously vary them. Although such experiments are not used in this thesis, they provide useful context and are conceptually related to the quasi-experimental features of the data used in Articles II and III. One class of studies randomises information provision, effectively eliminating search costs and attributing any remaining inertia to switching costs and behavioural frictions. Another class relies on 'forced choice' settings. For example, Handel (2013) exploits a natural experiment in which consumers were required to make an active choice, effectively removing inertia for one period. Comparing behaviour in forced-choice and default settings yields a non-parametric estimate of the inertia wedge. Similar approaches are used in Heiss et al. (2021) and are also employed in robustness checks in Article III.

Article III extends the approach adopted by Hortaçsu et al. (2017) by modelling consumer decisions in two stages: first, whether to pay attention to car insurance offers, and, second, whether to choose an insurance provider from a pre-set list of offers. The decision to pay attention and make a choice has two potential outcomes – attention or inattention – while the choice stage results in either retention or switching. Inattention always leads to retention, but retention can also arise from an informed decision to remain with the incumbent. Consequently, retention alone does not reveal whether attention was paid, whereas switching necessarily implies that the consumer has paid attention to alternative offers. The specification of the choice equation in Article III resembles that used by Hortaçsu et al. (2017), while the attention equation broadly follows Honka (2014), subject to certain data limitations.[6]

The empirical approach identifies separate parameters for both decision stages and allows for heterogeneity across individuals and over time by using panel data. The likelihood of paying attention to car insurance offers is modelled as a function of individual characteristics, car attributes, and prior experience with the current insurance provider. The two stages are simultaneously estimated using a Generalised Method of Moments (GMM) framework, where the moment conditions arise from the observed customer switch.

Contribution of Article III

The primary scientific contribution of Article III lies in its identification strategy: unlike most studies that must infer the set of options a consumer considers, this study utilises a setting in which the consideration set is observed and standardised. This allows for a precise measurement of inattention and provides string evidence that inertia is driven primarily by a failure to pay attention, rather than by brand loyalty or high switching costs.

Methodologically, the article advances the application of two-stage demand models (specifically the framework of Hortaçsu et al., 2017) by applying them to a 'quasi-experimental' setting. In typical market studies (e.g. health insurance), researchers must estimate what products a consumer *might* have seen. By contrast, in Kepp and Männasoo's (2025) study, the broker provides each lessee with a standardised list of mainly five offers. Because the researchers observe exactly what the consumer observes, they can isolate attention frictions (ignoring the renewal offers) from choice frictions (preferring the incumbent despite higher prices) with high accuracy. For this purpose, Article III implements a two-stage GMM model of attention and choice in a setting where consideration sets, offers from 11 insurers, claim histories, and socio-demographic characteristics are fully observed, and where monetary switching costs are negligible.

The article also contributes by providing robust empirical evidence that consumer inertia is a result of inattention rather than brand preference[7]. The model predicts that only 18.1% to 25.6% of customers pay attention to renewal offers, implying that attention is rare. At the same time, conditional on attention, choice behaviour is strongly rational: consumers are highly price-elastic and switch to the cheapest offer in around

[6] Honka (2014) uses a slightly broader list of socio-demographic variables, along with customers' credit history and consumer survey information, but does not include claims data.

[7] Brand in insurance markets carries a specific meaning distinct from fast-moving consumer goods: it primarily reflects trust in the insurer's financial strength, claims-handling reputation, and service reliability – dimensions that are difficult to observe ex-ante and are only revealed through experience (Schlesinger & von der Schulenburg, 1993a). In the Estonian car insurance context, all participating insurers are licensed and solvent, and product terms are standardised by the broker. This reduces brand's informational role and helps explain why its empirical effect on choice is statistically present but economically modest.

70% of cases, with only modest residual brand effects. Moreover, the article documents heterogeneity in attention, showing how attention varies with tenure, car value, past relative insurance premiums, claims, and demographic characteristics. All attention and choice estimates are validated using three complementary strategies: a forced-attention subsample, a young-customer subsample designed to mitigate left-censoring and state dependence, and a regulatory shock in claim handling that provides exogenous variation in choice factors.

Relative to Hortaçsu et al. (2017), Article III contributes by applying a similar two-stage framework in a quasi-experimental setting with nearly fully observed choice sets and no pecuniary switching costs, thereby sharpening identification of attention versus choice frictions. Relative to Honka (2014) and Kiss (2019), it shifts the focus from search and switching costs to attention, and relies on broker-generated offer sets rather than imputed consideration sets.

Notably, the article does not claim to fully solve the rational inattention problem but rather provides new evidence on how attention and choice frictions interact in a specific car insurance market with low monetary switching costs and transparent offers. Its findings complement the broader rational inattention literature by showing that, even in such a favourable environment, limited attention can remain the dominant driver of inertia.

It is also useful to contrast this approach with Brown and Jeon (2024), who address a similar identification problem using a different structural strategy. While Article III separates attention and choice into a two-stage GMM framework following Hortaçsu et al. (2017), Brown and Jeon embed the endogenous information acquisition decision directly into the demand model using the rational inattention framework of Matějka and McKay (2015). Their approach allows the information cost parameter to be estimated alongside the choice parameters, whereas Article III treats the attention decision as a separate logit stage. The two approaches offer complementary advantages: Article III's two-stage structure is more transparent and allows rich heterogeneity in attention determinants (including claims history and car characteristics), while Brown and Jeon's integrated framework provides tighter micro-foundation for the information acquisition decision. Future work could explore whether integrating the RI cost function into the Estonian broker setting yields similar attention estimates.

3. Results and discussion

3.1 Article I

Article I, described in Section 2.1.1, uses System-GMM estimation on a panel of over 10,000 European manufacturing companies to identify how fixed and current investment interact with cyclical adversity to shape risk-adjusted ROA and ROIC.

The GMM estimation results provide robust support for the investment irreversibility argument during periods of economic distress. The study finds a consistently negative and significant interaction effect between fixed tangible investment and cyclical adversity, measured as a negative value-added gap, and confirms that the financial performance of companies, measured by ROA and ROIC, deteriorates when irreversible investments are made or held during deep cyclical gaps. The detrimental effect of fixed investment on financial returns becomes statistically significant when the real gross value added gap falls between 1% and 3% below its trend growth level.

The adverse impact on returns is particularly strong when a negative demand shock is coupled with high uncertainty in producer prices. While price uncertainty alone does not significantly harm performance, its combination with a cyclical slump creates a powerful reinforcement mechanism that suppresses financial returns. Descriptive evidence further suggests that companies maintaining higher levels of current investment (working capital) perform significantly better during crises. This aligns with the theory that current assets can help absorb some of the ‘rigidity’ or irreversibility constraints imposed by fixed capital.

These findings resonate with several recent contributions. The result that producer price uncertainty alone does not significantly harm performance, but becomes damaging when combined with a demand contraction, is consistent with Drakos and Tsouknidis (2024), who show that the amplifying role of asset irreversibility operates through global economic uncertainty rather than through sector-specific uncertainty. It also aligns with Kahle and Stulz (2013), who argue that the demand shock and uncertainty, rather than credit supply alone, were the primary drivers of the investment collapse during the 2008–2009 crisis. The finding on the buffering role of current investment and working capital is supported by Vardar and Cifter (2025), who independently document that working capital acts as a buffer against uncertainty for European firms using a more recent sample period (2013–2023).

The non-linear threshold finding – that the negative interaction effect becomes significant at around a 1–3% output gap but imprecise beyond 4% – has not been directly replicated in subsequent studies, which typically model uncertainty–investment relationships as linear or rely on binary crisis indicators. This non-linearity therefore remains a distinctive empirical contribution. However, Kolev and Randall (2024), using firm-level survey data, report that firms citing uncertainty as a major impediment show a 3-percentage-point lower investment rate, which is broadly consistent with the magnitude of effects documented in Article I for moderate output gaps.

The article concludes that a ‘reinforcement mechanism’ exists between cyclical adversity and market imperfections, which gives rise to credit and irreversibility constraints. For corporate managers, this implies that investment decisions must be evaluated against macroeconomic output gap and price volatility indicators. Because fixed investments may generate negative returns in the short term during a slump, managers often postpone capital formation, which can inadvertently slow down recovery at both the company and national levels.

Article I quantifies the performance consequences of the option value of waiting. In the presence of irreversibility and financial frictions, deep adverse output gaps in the range of -1% to -3%, combined with elevated price volatility, create conditions where additional fixed capital reduces risk-adjusted returns, whereas maintaining liquidity and current assets helps buffer shocks. In this way, the article fills the gap on micro-level, risk-adjusted performance effects of investment irreversibility under cyclical adversity identified in Sections 1 and 2.1.2.

Subsequent research has identified dimensions of heterogeneity that Article I does not fully exploit. Baum, Caglayan, and Talavera (2008, 2010) show that the investment–uncertainty relationship varies significantly with a firm's leverage position, with highly leveraged firms exhibiting stronger negative responses. While Article I controls for the equity-to-assets ratio, allowing the investment–slump interaction to vary explicitly by leverage category could reveal whether the irreversibility effect is concentrated among more financially constrained firms. Similarly, Kim and Kung (2017) introduce asset redeployability as a firm-level measure of effective irreversibility, showing that firms with more redeployable assets invest more during downturns. Article I treats all fixed tangible investment as subject to similar irreversibility constraints; incorporating asset specificity measures could therefore sharpen the test of the irreversibility hypothesis. These extensions represent promising avenues for future research that build on Article I's framework.

3.2. Article II

Article II, described in Section 2.2.2, explores switching behaviour and claim-type-specific learning in the Estonian broker setting, where monetary search and switching costs are negligible and choice sets are fully observed.

If search and switching costs could be explained purely in monetary terms, this market would be highly fluid, with rational consumers constantly opting for the cheapest option. Yet, Article II shows that inertia persists. The average probability of a consumer switching providers is only around 11%, and this low rate – despite near-zero pecuniary search and switching costs – provides strong evidence that the friction is not primarily monetary. Instead, the dominant barrier appears to be attentional: most consumers simply do not engage with the renewal offers they receive. This gap between the high switching rates predicted under frictionless conditions, and the stability observed in Estonia suggests that previous literature may have underestimated the power of passive inattention (Handel, 2013) and non-pecuniary switching costs (Burnham et al., 2003).

Despite this high baseline inertia, the study finds strong evidence that consumers remain rational actors when they pay attention. The response to price gaps is sharp and logical. Specifically, consumers are far more sensitive to the market gap (the difference between their current price and the cheapest available option) than to changes in their own renewal price. A 1% increase in the incumbent's price raises the probability of switching by only around 0.2 percentage points. However, a 1% gap between the incumbent's offer and the cheapest alternative increases switching probability by roughly 2 percentage points, a tenfold stronger response. This nuance refines previous conclusions regarding consumer 'mistakes'. In Estonia, consumers appear to ignore small savings but respond strongly when potential savings are large enough to justify the effort of switching.

Perhaps the most novel contribution of Article II is the refinement of the learning hypothesis. Earlier studies, such as those by Israel (2005) and Miravete and Palacios-Huerta (2014), argue that claims act as learning events that reveal service quality and may trigger switching if consumers are dissatisfied. Article II shows that the cause of the claim triggers asymmetric responses. When consumers experience a claim caused by a third party (where they are the victim), switching rates increase, likely reflecting frustration or hassle associated with the process. Conversely, when the claim is self-induced (where the driver is at fault), switching rates significantly decrease.

This reduction in switching following self-induced claims provides a compelling contrast to classic asymmetric information models (e.g. Cohen, 2005), which predict that at-fault drivers will opportunistically switch to 'flee' their poor claims record and avoid premium penalties at renewal. The data are consistent with two competing mechanisms. The first is an adverse selection channel: a consumer who has caused a claim knows their own current risk type has worsened and may rationally stay with the incumbent to avoid having to disclose this information – or face higher pricing – with a new insurer. The second is a reciprocity channel: the consumer may perceive the insurer's decision to cover their own mistake as a form of goodwill, generating a loyalty response or 'gratitude' toward the incumbent (Soscia, 2007). Both channels predict the same observed pattern, and distinguishing between them would require information on how premium penalties are applied at renewal – data that are not available in the current setting. Article II emphasises the reciprocity interpretation as the more novel contribution, while acknowledging that the adverse selection channel provides a complementary rational explanation. This interpretive ambiguity is itself a finding, as it highlights a mechanism that future research – combining administrative data with survey evidence on consumer perceptions – could identify more directly.

From a thesis-level perspective, Article II provides high-quality micro evidence on switching behaviour and learning from claims in a market with fully observed choice sets and no pecuniary switching costs. By demonstrating that switching remains relatively rare, that behaviour is strongly price-driven conditional on attention, and that claim-type-specific learning generates asymmetric lock-in effects, it fills the gap on triggers of switching and reduced-form learning identified in Sections 1.2 and 2.2.3.

3.3. Article III

Article III extends the reduced-form analysis of Article II. While the context remains the same (Estonian leased cars in a standardised broker setting), the authors apply a two-stage structural model (based on Hortaçsu et al., 2017) to mathematically separate 'attention' (the decision to consider alternatives) from 'choice' (the selection of a provider conditional on attention).

The study reveals that the primary friction is not dissatisfaction with the product but simply a failure to engage with it. Previous studies such as Honka (2014) estimated that if search costs were removed, switching rates in car insurance would surge dramatically. Article III challenges this prediction in the Estonian context. The model estimates that only around 18–26% of consumers even pay attention to their renewal offers in a given year. Once a consumer overcomes their inattention, they become highly sensitive to price: the price coefficient in the choice stage implies strong price elasticity of switching conditional on attention, while insurance provider brand exerts only a modest influence. This suggests that what looks like 'brand loyalty' in the aggregate switching rate is primarily explained by inattention rather than by strong conditional brand preferences:

most consumers do not switch because they never engage with the alternative. Genuine preference-based loyalty, which is a willingness to pay a premium for the incumbent even after active comparison, plays a secondary role in driving observed market outcomes, though it is not absent.

This finding also raises a broader implication for the consumer switching literature. In settings where attention is not separately identified, estimates of brand loyalty and switching costs may conflate true preferences with passive inertia. In other words, part of what has been interpreted as 'brand loyalty' in prior studies may reflect inattention, implying a potential measurement bias that Article III is particularly well suited to uncover.

The attention decay pattern documented in Article III is consistent with findings from other markets. Einav, Klopack, and Mahoney (2025) document a similar pattern in subscription services, where attention probability varies from 4% to 50% depending on the service type, with lower attention for more established subscriptions. Moreover, a study by Nguyen (2025) finds a comparable decline in attention over tenure in subscription settings, while Heiss et al. (2021) show that attention to Medicare Part D choices is concentrated around specific events (such as plan changes or health shocks) rather than being uniformly distributed over time. These converging findings across markets suggest that tenure-dependent attention decay is a robust empirical regularity rather than an artefact of the Estonian car insurance setting.

Conditional on attention, the mean switching probability is approximately 30%, and this conditional switching rate is remarkably stable across subsamples, including single-switcher and multiple-switcher groups. Differences between these groups are therefore driven primarily by attention, not by differences in choice parameters. Attention decreases with tenure and car value, and increases with previous relative overpayment and claims, indicating that both economic and experiential factors shape the likelihood that consumers review their options. This gradient mirrors findings from financial markets: Grinblatt, Keloharju, and Linnainmaa (2012) show that higher-IQ Finnish investors are significantly less subject to behavioural inertia and more likely to act on available information, with the gap between knowing and acting largest among lower-stakes, habituated decision-makers. In both settings, inertia concentrates among those for whom the decision has become routine and its salience low.

The article further strengthens its conclusions through a set of robustness checks. A subsample of customers who were forced to pay attention due to changes in contract terms or non-automated offers confirms that the estimated attention probabilities are plausible and likely conservative. A subsample of young customers is used to reduce left-censoring concerns, and a regulatory shock in claim handling provides exogenous variation in choice factors. None of these checks overturn the main findings.

Article III shows that, even in a highly transparent, standardised market with negligible switching costs, attention remains scarce. Inertia therefore arises primarily from limited attention rather than from strong intrinsic preferences for incumbents. In doing so, the article provides new evidence on the decomposition of inertia into attention and choice components in a quasi-experimental car insurance market, thereby addressing the gap on separately measured attention and choice frictions identified in Section 2.2.3. The findings also align with the theoretical framework of Mackowiak and Wiederholt (2025), who demonstrate that the utility of being informed is low relative to the cognitive cost of attention.

From a cross-article perspective, Article III provides the mechanism underlying the inertia documented in Article II. While Article II shows that switching is rare but strongly price-driven when it occurs, Article III demonstrates that most consumers do not reach the stage at which they compare prices. Once they do, though, they behave in a way that is broadly consistent with the rational benchmark. This mapping from attention probabilities to switching-conditional-on-attention rates links the empirical estimates in this thesis to attention parameters in the theoretical literature, such as the average attention intensity discussed by Gabaix (2019) and the rational inattention models surveyed by Mackowiak et al. (2023).

4. Conclusions and implications

4.1. Companies' performance

Article I examines how corporate investment decisions interact with macroeconomic cyclical conditions – output gaps and producer-price volatility – to shape risk-adjusted financial performance (ROA and ROIC). By utilising system-GMM estimations to control for unobserved variables and endogeneity, the research provides a robust empirical foundation for understanding why investing during economic downturns can often yield counterintuitive and detrimental financial results.

At the heart of the study's findings is the concept of investment irreversibility, grounded in the theoretical mechanism introduced in Section 1.1.1. The theory posits that in incomplete markets, capital investments in fixed assets are often 'sunk costs', i.e. expenditures that cannot be easily recovered or liquidated without significant loss. The evidence suggests a clear negative interaction between cyclical adversity and fixed investment. When a company commits to major projects during an aggregate slump – characterised by high uncertainty in producer prices and a significant gap in value-added growth – the financial returns on those investments tend to suffer. This effect is most pronounced when the real value-added gap falls within 1–3% of its trend growth level, marking a specific 'danger zone' where the risks of capital commitment are at their highest. For deeper downturns beyond a 4% gap, the dynamics may differ, but such episodes are too infrequent in the sample to support statistically robust conclusions.

This phenomenon creates a reinforcing mechanism that links macroeconomic instability with market imperfections. As economic uncertainty rises, the 'option to delay' becomes more attractive to managers. At the same time, tightening credit constraints amplify the risk of being locked into unproductive capital. As a result, firms rationally postpone investment. While this is a rational decision at the firm level, it generates a collective slowdown in capital formation, thereby dampening aggregate recovery and potentially prolonging downturns.

The COVID-19 pandemic and subsequent economic disruptions further highlight the relevance of these findings. Research using European firm-level data from the pandemic period has confirmed that uncertainty depresses investment and harms financial performance through channels consistent with those documented in Article I. Kolev and Randall (2024) report that firms facing high uncertainty exhibit significantly lower investment and employment growth. In addition, Coad et al. (2023) find that R&D-intensive and small firms – those most exposed to irreversibility and financial constraints – were disproportionately affected by COVID-19 pandemic uncertainty. These findings suggest that the reinforcement mechanism between cyclical adversity, irreversibility, and credit constraints identified in Article I is not specific to the 2008–2009 crisis but operates across different types of aggregate shocks.

The article also highlights the importance of current investment and liquidity buffers. Companies with higher levels of current assets and working capital are better positioned to absorb shocks and maintain positive risk-adjusted performance during adverse phases of the cycle. In other words, flexibility in the balance sheet can partly offset the rigidity created by irreversible fixed assets. This interplay between fixed investment, current assets, and debt flows underscores that performance under uncertainty depends not only on *how much* firms invest, but also on *what* they invest *in* and how they finance it.

These findings carry important implications for both corporate investment strategy and public policy. At the company level, they highlight the need to evaluate investment decisions and evolving performance risks against the uncertainties in macroeconomic dynamics. Specifically, companies should: (i) build balance sheet liquidity during upswings to preserve optionality during downturns; (ii) prioritise reversible current investment (working capital, flexible capacity) over fixed capital during periods of elevated price uncertainty; (iii) monitor output gap indicators and producer price volatility as leading signals of the 'danger zone' identified in Article I (1–3% below-trend output gaps); and (iv), where investment cannot be deferred, consider staged or modular investment approaches that limit upfront sunk costs. From a policy standpoint, the research suggests that governments play a vital role in mitigating the cyclical adversity that discourages investments and prolongs recessions. Most importantly, public support should be targeted toward viable firms operating under credit constraints and adverse macroeconomic conditions. More broadly, addressing the irreversibility 'trap' requires a balance between prudent capital management at the firm level and effective macro-financial stabilisation at the policy level.

Recent research has begun to operationalise these implications. Kalemli-Özcan et al. (2022) show that the debt overhang channel operates independently of aggregate demand effects, suggesting that policies aimed at reducing firm-level leverage during crises can directly alleviate the investment constraint without requiring a full demand recovery. Furthermore, Kumar et al. (2023) demonstrate that exogenous reductions in perceived uncertainty cause firms to increase investment, supporting the role of credible policy communication. At the firm liquidity level, Masso, Meriküll, and Vahter (2013) provide complementary evidence from Estonia's unique shift to distributed profit taxation in 2000, which eliminated tax on retained earnings. Using Baltic firm-level data and difference-in-differences estimation, they show that the reform caused firms to accumulate liquid assets and reduce debt financing, and that these balance-sheet adjustments contributed positively to firm survival during the 2008–2009 crisis. Their finding resonates with Article I's result that current investment and working capital buffers mitigate the adverse performance effects of irreversible fixed assets during downturns and suggests that tax and regulatory frameworks encouraging internal liquidity accumulation can serve as a structural counterweight to the irreversibility trap.

Together, these findings reinforce the argument that policies addressing both the demand gap and the uncertainty environment – rather than targeting one dimension alone – are most likely to prevent the performance deterioration associated with irreversible investment during downturns. The option value framework developed in Section 1.1.1 suggests that these policies operate through four distinct levers, each targeting a different determinant of the option value of waiting.

The first lever is reducing macroeconomic and regulatory policy uncertainty directly. Baker, Bloom, and Davis (2016) construct an Economic Policy Uncertainty index from newspaper coverage, legislative expiry dates, and forecaster disagreement and show that policy-specific uncertainty exerts a negative effect on investment independently of general economic conditions. This finding supports the case for credible multi-year fiscal frameworks, stable regulatory environments, and unambiguous central bank forward guidance as structural investment promotion tools. Each of them reduces the variance of the policy environment that companies must forecast when evaluating irreversible commitments, and thereby lowers the investment trigger without requiring direct expenditure.

The second lever targets the financial amplifier of the option value. Bernanke, Gertler, and Gilchrist (1999) formalise the financial accelerator: in downturns, rising external finance premia increase the effective cost of investment relative to waiting, so that the option value of delay is amplified beyond what irreversibility alone would predict. Countercyclical credit instruments like government-backed loan guarantees, development bank lending, and advance purchase commitments in public procurement can compress this premium and narrow the band of inaction without requiring broad demand stimulus, which is consistent with the Article I finding that debt-financed fixed investment during the danger zone is especially harmful to risk-adjusted returns.

The third lever directly shortens the time value of the waiting option through investment incentives with binding expiry dates. Time-limited accelerated depreciation, investment tax credits with sunset clauses, and capacity support conditional on commissioning within a specified window reduce the value of waiting by making delay costly: a firm that postpones beyond the deadline forfeits the benefit, restoring the option value calculus in favour of immediate commitment. Leahy and Whited (1996) provide complementary evidence that idiosyncratic firm-level uncertainty raises the investment trigger by more than aggregate uncertainty, suggesting that policies targeting firm-level information clarity can be at least as effective as aggregate macro stabilisation at bringing irreversible investment forward.

Empirical support for this lever is substantial. Zwick and Mahon (2017) exploit US bonus depreciation episodes between 2001 and 2010, finding that accelerated depreciation raised equipment investment by 10.4% and 16.9% in the two windows respectively, with small and financially constrained firms responding approximately 95% more than large ones — a heterogeneity consistent with the financial frictions mechanism central to Article I. Comparable evidence emerges from the UK's 2021–2023 super-deduction, a 130% first-year capital allowance on plant and machinery, where Bank of England Decision Maker Panel data indicate that approximately two-thirds of the resulting investment increase of around 6% reflected genuinely additional investment rather than timing shifts (Anayi et al., 2021). A critical conditioning result is that investment incentives are substantially less effective when deployed during periods of elevated uncertainty. Güçeri and Albinowski (2021) exploit a natural experiment in which two near-identical investment subsidies were introduced in the same country two years apart — once during stability, once during high uncertainty — and find that uncertainty-exposed firms adopt a 'wait-and-see' posture despite generous incentives, while firms sheltered from uncertainty still respond strongly. This result directly mirrors the dampening mechanism formalised by Bloom, Bond, and Van Reenen (2007) and implies that the timing and permanence of investment incentives matter as much as their size: a temporary scheme whose renewal is uncertain may itself constitute a source of policy uncertainty that partially offsets the trigger reduction it intends to achieve (Stokey, 2016).

A fourth lever, directly connected to Article I's use of excess producer-price volatility as the second dimension of cyclical adversity, operates through the reduction of input-cost uncertainty. Londono, Ma, and Wilson (2023) decompose the investment-depressing effect of inflation uncertainty into a discount rate channel and a cash-flow uncertainty channel, both consistent with option-pricing theory, and find that the pass-through to investment is particularly pronounced in energy-intensive manufacturing branches. Policies that reduce the variance of energy and raw material costs — through long-term power purchase agreements, strategic commodity reserves, or regulated price-corridor mechanisms for industrial electricity — directly compress the GARCH-estimated producer-price volatility that Article I identifies as a determinant of the danger zone. This rationale is especially pertinent in light of the 2021–2022 European energy price crisis, during which a surge in gas and electricity price volatility simultaneously depressed manufacturing margins and raised the option value of deferring fixed investment across industries comparable to the Article I sample. An important caveat, however, is that the transition to renewable energy may, in the absence of adequate grid flexibility, storage, and cross-border interconnection, substitute fuel-price risk with supply-intermittency risk, leaving the core mechanism of Section 1.1.1 structurally intact and underscoring the need to treat energy transition policy and investment stabilisation policy as jointly designed.

4.2. Consumer inertia

Articles II and III draw on the same broker dataset but address distinct research questions: Article II focuses on the triggers of switching, while Article III structurally decomposes inertia into attention and choice.

Findings on switching and learning in Article II
Article II documents the drivers of switching, focusing on price differentials, claim-type learning, and consumer characteristics. It focuses on one specific aspect of potential frictions, namely learning about the insurer's service quality. To achieve this, it explores to what extent switching is driven by direct monetary effects, how much is attributable to observed heterogeneity, and how much can be explained by the customer learning about the quality of the service.

In general, there is inertia, and the average probability of a customer switching service provider at renewal is around 11%. As expected, direct monetary gains are a significant driver of switching. A change in the price offered by the incumbent insurer relative to the previous year is statistically significant, but the difference between the price offered by the incumbent and the cheapest alternative has a far greater impact. A rise in the incumbent price of 1% at renewal makes switching roughly 0.2 percentage points more likely on average than the base rate, while a 1% increase in the gap between the incumbent offer and the cheapest option raises the likelihood of switching by roughly 2 percentage points. Even if the overall switching rate is not particularly high, the responses to changes within the choice set are more pronounced than those to changes in the default option.

Article II shows that overall inertia is lower than indicated by earlier studies of adjustment costs, and behaviour consistent with *homo economicus* is visible in this setting. Since there are no direct monetary costs of search or switching, the remaining theoretical explanations for inertia relate primarily to information processing and learning. Insurance is an intangible good, and consumers can only experience it directly when a claim occurs. However, Article II does not find a statistically significant or pronounced relationship between a previous claim and the probability of switching. Once claims are classified into different categories, consumers who experienced a claim caused by a third party are more likely to switch than those who experienced other types of claims.

If consumers experienced a self-induced claim, they were more likely to stick with their previous choice, even after taking into account interaction terms designed to control for the price impact of the claim on the renewal price of the incumbent insurer for the next period. This outcome is novel and points to the need for further research into the psychological drivers of switching behaviour and, more broadly, their role in information processing and search frictions.

The asymmetric response to claim types documented in Article II remains, to our knowledge, unique in the literature. No subsequent study has replicated the finding that self-induced claims reduce switching while third-party-induced claims increase it. This novelty is noteworthy because the growing literature on consumer emotions and service recovery (building on Soscia, 2007) has mostly focused on satisfaction and complaint behaviour related to reciprocity rather than on how the cause of a service interaction affects subsequent provider choice. The claim-type distinction introduced in Article II thus opens a new research avenue that connects the insurance switching literature with the behavioural service quality literature in a way that has not yet been fully explored.

Findings on inattention in Article III

Article III found considerable consumer inertia and inattention in car insurance among car leasing customers in a competitive market with very low switching costs. The insurance distribution system is characterised by high transparency and substantially reduced information processing costs for the consumer. Nevertheless, consistent with Honka (2014), Article III establishes a high degree of inattention, which may suggest further behavioural frictions beyond information-processing costs. More than three-quarters of customers who switch choose the lowest price offer from their choice set, while only 54% of non-switchers renew at the minimum price of their set of offers. Consumers who switch pay nearly 15% lower premiums with the new provider compared to the offer from their past provider in the current year, while those who remain with their incumbent provider renew at a price that is on average 6% lower than the previous year's offer.

Predicted attention has a right-skewed distribution, with the mean ranging between 18% and 26%, depending on whether the sample includes only single switchers or also multiple switchers. Of consumers who pay attention, roughly 30% decide to switch. Attention is highly heterogeneous and depends on customer tenure, individual preferences, and background characteristics. The results for the subsample of customers under 34 years old and with no previous switching history align well with the predicted ranges for the broader samples, which suggests that the results are not driven by left-censoring or unobserved past experiences. Moreover, robustness checks using a subsample of forced-attention customers and a regulatory change in claims handling further confirm the plausibility of the attention and choice parameter estimates.

Conditional on a consumer deciding to consider alternative offers, price is a very strong determinant of consumer choice, whereas insurance provider brand has only a weak positive effect on consumer choice. None of the determinants of the choice decision differ between single switchers and more experienced multiple switchers. This suggests that learning primarily manifests in the attention stage of the decision process and is less relevant for the choice stage itself. Time trends exhibit a modest increase in consumers' propensity to pay attention, which may be a positive signal of improving customer awareness. Whether this trend continues and is related to increased financial literacy, openness, transparency, and competitiveness in the insurance market remains to be seen.

Taken together, Articles II and III show that the Estonian MOD market, particularly in the leasing-company setting, can be viewed as a real-world laboratory for studying inertia when monetary search and switching costs are minimal. Article II demonstrates that switching is relatively rare but strongly price-driven and influenced by claim-type-specific learning, while Article III shows that limited attention is the main source of inertia, with behaviour conditional on attention broadly consistent with rational choice. In this way, the consumer-side essays contribute to an emerging 2020s literature on rational inattention and behavioural frictions using insurance markets data.

Regulatory implications

The cumulative effect of consumer inertia is substantial consumer detriment and suboptimal market functioning. The thesis' findings carry direct policy relevance for insurance market regulators, both in Estonia and in comparable markets. In other markets, regulators have already begun to implement interventions designed to counteract the drivers of inertia across different segments. These interventions have generally focused on three areas: improving information disclosure, reducing switching costs, and, in some cases, direct market intervention.

For policymakers, inertia presents a complex challenge that requires careful consideration. A key task is to distinguish the underlying source of inertia. If inertia is driven by search costs (as in the insurance and electricity markets discussed earlier), policies should focus on standardisation and on increasing the salience of automated comparison tools, or on evaluating the costs and benefits of consumer-directed advice. If inertia is instead driven by switching costs (as in banking, based on studies referenced earlier, or in telecom markets such as the Estonian mobile operator market at the time of writing), then portability and interoperability become the key policy levers.

To combat rational inattention in the field of insurance, some countries have adopted regulations to make crucial information more salient – for instance, requiring insurers to prominently display the previous year's premium alongside the renewal quote on the same document serves as a powerful nudge. This simple disclosure dramatically reduces the cognitive cost of identifying a price increase, prompting a more active search process (Financial Conduct Authority, 2020). However, such measures only address price transparency and cannot easily mitigate the uncertainty surrounding service quality – a key driver of inertia for experience goods.

More targeted procedural interventions, such as standardised comparison tools and streamlined switching services – analogous to Open Banking initiatives in financial services – reduce the effort required to change providers without requiring direct price regulation. Brown and Jeon (2024) provide direct evidence that reducing the number of available options in a standardised comparison table can raise consumer welfare not only through improved choice quality but also through savings in information processing costs, a result that lends direct institutional support to the broker-standardised format of approximately five offers examined in Articles II and III.

In more extreme cases, regulators have moved to ban the outcomes of inertia-based pricing. Following its market study, the Financial Conduct Authority (2021) implemented rules that ban price walking, forcing insurers to offer renewing customers a price no higher than they would be offered as a new customer. This represents a direct intervention to protect inert consumers from price discrimination. A related phenomenon is observable in the dataset used in this thesis. In the broker-mediated setting, where offers are standardised and presented comparably, much of the search and cognitive effort is already removed. In addition, because insurers must compete for each renewal as if it were a new customer, the setting itself creates incentives that limit inertia-based pricing.

Recent research on the 'intention–action gap' (Gravert, 2025; Miller et al., 2023) shows that consumers who express an intention to switch service provider frequently fail to act at renewal – a pattern that is conceptually distinct from status-quo bias in that the consumer has formed an active intention but is prevented from acting by present bias. While status-quo bias calls for redesigning defaults, the intention–action gap calls for reminders and simplifications of the switching process. Together, both mechanisms point toward the necessity of 'smart defaults' – policies that harness inertia for good by setting the path of least resistance toward the welfare-maximising option, such as auto-enrolment in lower-cost plans, rather than relying on the imagined discipline of the 'active consumer'.

As digital intermediaries and AI agents (‘searching bots’) begin to act on behalf of consumers, direct search costs may decline substantially. Whether this will eliminate inertia or instead shift it toward new forms of algorithmic bias remains an open question for future research.

Consumer inertia is a structurally embodied phenomenon, not merely a symptom of consumer apathy. It arises from a rational, if bounded, calculation of costs and benefits in a world of limited cognitive resources. The theory of rational inattention provides a robust framework for understanding this calculus, while principles from behavioural economics, such as loss aversion and status quo bias, illuminate the predictable psychological patterns that result.

The car insurance market serves as a compelling case study, demonstrating how market structures can evolve to exploit these tendencies, leading to significant financial harm for consumers. A rough estimate of the financial harm to consumers can be derived from Articles II and III's findings: if approximately 74–82% of consumers are inattentive at any given renewal, and the average price gap between the incumbent and the cheapest alternative is approximately 6%, an inattentive consumer on a €400 annual premium would forgo roughly €24 per year in savings. Across the Estonian MOD market with approximately 200,000 policies and an average annual premium of approximately €400 (the market average over the sample period), this implies foregone consumer savings in the order of €3.8 million annually (200,000 × 0.8 × €24)

This is a non-trivial welfare cost in a small market with a transparent and competitive broker channel in only one business line. The above estimate is conservative, as it does not account for multi-year compounding of inertia-based price drift. While market-based solutions are preferable, the scale of consumer detriment has necessitated regulatory interventions in some markets aimed at lowering cognitive costs, increasing the salience of price changes, and, in some cases, directly prohibiting exploitative pricing strategies like in the U.K.

Although insurance brokers provide information to customers (sometimes at a cost), they also generally reduce the search cost. Future research into financial literacy and the impact of new technologies, such as AI-powered comparison tools, might shed additional light on consumers' ability to manage information and overcome the powerful force of inertia.

From a cross-article perspective, the thesis demonstrates that frictions in economic decision-making operate at both the company and consumer levels through structurally analogous mechanisms, even if their surface manifestations differ. For companies, the binding constraint is the irreversibility of fixed capital: a sunk-cost investment made during a period of cyclical adversity cannot be unwound without loss, so the option to delay is valuable and firms rationally exercise it. When aggregate paralysis sets in, companies that have already committed fixed investment face deteriorating risk-adjusted returns with no exit (Article I). For consumers, the binding constraint is limited attention: the option to delay evaluating renewal offers is costless to exercise in any given period, but each period of inattention forfeits an average saving of approximately 6% of the premium, and the compounding of these deferrals generates the welfare loss documented in Articles II and III.

In both cases, the information needed to identify the better option is available in principle, but the friction raises the cost of acting on it above the threshold at which action is triggered. Companies can observe that the economic environment is adverse, and inattentive consumers could, if they paid attention, identify the cheaper insurer from the broker comparison table. The option value of waiting, originally developed in the context of irreversible investment under macroeconomic uncertainty (Dixit & Pindyck, 1994; Pindyck, 1991), thus provides a unified theoretical vocabulary for both phenomena: it is high when friction is high, when uncertainty about the payoff to acting is high, and when the cost of the status quo is insufficiently salient. Klemperer (1995) makes this parallel explicit in the switching cost literature, showing that the consumer's option to delay switching is formally analogous to the firm's real option to delay investment, with accumulated relational capital playing the role of the sunk cost that raises the exit threshold.

This shared structure has a common policy implication that the thesis-level findings make concrete. Reducing inertia requires lowering the option value of waiting by targeting its underlying determinants, rather than simply improving the attractiveness of alternatives. Stimulating demand alone does not restart firm investment if policy uncertainty keeps the trigger threshold high (Baker, Bloom, & Davis, 2016), just as offering a cheaper insurance alternative does not trigger switching if the consumer never attends to the renewal offer. In both cases, the most effective interventions are those that reduce the cost of acting: credible macroeconomic and regulatory stability for firms (Bloom, Bond, & Van Reenen, 2007), and salience-enhancing disclosure, smart defaults, and friction-reducing intermediaries for consumers (Thaler & Sunstein, 2008; Financial Conduct Authority, 2021). The thesis contributes to both literatures by providing large-sample micro evidence on the performance and welfare costs of inaction under friction, thereby giving empirical support to the theoretical case for such interventions.

Limitations and further research

The thesis has several limitations that are worth acknowledging, though in some cases the features that limit generalisability also constitute the source of the empirical identification advantage.

The company-level analysis in Article I is confined to manufacturing firms in EU member states observed in the Orbis database over the period 2005–2018. It provides broad cross-country micro-level coverage that is rare in the investment–performance literature, but the findings are most directly generalisable to European manufacturing sectors with comparable institutional and financial market characteristics. Extension to service industries, non-EU markets, or the post-2018 period, which includes the COVID-19 shock and the energy price crisis, would require additional analysis and may yield different threshold effects, given structural differences in asset specificity and credit market depth. For very deep recessions beyond a 4% output gap, the non-linearity may take a different form, but such episodes are sufficiently rare that the current dataset does not support statistically precise conclusions in that range. These therefore represent genuine boundaries of external validity that future large-sample studies, covering longer time horizons or broader sectoral scope, could address.

For Articles II and III, the Estonian broker-mediated leasing setting is highly specific. At the same time, it is precisely this setting that generates the identification advantages of the research design. The quasi-experimental structure of the data – with fully observed standardised offer sets, exogenous renewal timing, negligible monetary switching costs, and a structurally impartial broker – removes the most common confounders that plague inertia studies in other markets. Rather than being a limitation, this constitutes the main source of internal validity of the findings. The key external validity question is whether the estimated magnitudes of inattention and the claim-type asymmetry in switching generalise to larger markets, alternative distribution channels, or other product categories such as health insurance, energy, or telecom services. Applying comparable attention-choice decompositions in these settings would test the scope of the patterns documented here, and the institutional template of the Estonian leasing-broker model could itself serve as a benchmark for what transparent intermediation can achieve in terms of reducing search frictions.

The psychological mechanisms proposed in Article II – gratitude and dissatisfaction as responses to different claim types – are inferred from asymmetric switching patterns but are not structurally identified. The finding that self-induced claims reduce switching while third-party claims increase it is, to our knowledge, unique in the literature, and the mechanism linking claim attribution to provider loyalty remains an open question. Future research combining administrative claims records with survey data on consumer perceptions, or using field experiments with randomised claim outcome information, could separate the rational updating channel from the emotional attribution channel directly.

Finally, the identification of attention in Article III rests on structural assumptions typical for two-stage discrete choice models. While extensive robustness checks support the parameter estimates, a fully randomised experimental design would provide the strongest possible validation. As AI-based, consumer-triggered recommendations spread, new data sources may enable more precise real-time measurement of consideration set formation and attention allocation, which, in turn, may eventually redefine the economics of consumer inertia in intermediated markets.

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Abstract

Essays on Company Decisions Under Uncertainty and Inertia in Consumer Choice

Individuals and companies make intertemporal economic decisions – such as investment decisions and insurance consumption choices – under substantial uncertainty about the expected outcomes. These decisions are often shaped by market and behavioural frictions that delay or distort adjustment to changing economic and market conditions. This thesis examines two manifestations of such frictions. First, it studies how irreversible fixed investment under macroeconomic uncertainty and credit constraints affects companies' financial performance. Second, it explores how inattention and inertia lead to suboptimal consumer choice in car insurance. The unifying theme is that economic agents under incomplete information face costs of action – irreversible sunk investment capital for companies and cognitive cost of attending to renewal offers for consumers – that generate departures from the frictionless benchmark. The thesis consists of three empirical essays. Article I investigates European manufacturing companies' investments and performance over economic cycles, while Articles II and III focus on consumer attention, choice, and switching in the Estonian car insurance market.

The prior literature on companies' investment decisions has primarily studied how irreversibility and macroeconomic uncertainty affect the volume and timing of investment (Bernanke, 1983; Dixit & Pindyck, 1994). Specifically, the literature lacks cross-country micro-level empirical evidence of how the interaction between irreversible investment, debt flows, and cyclical fluctuations translates into risk adjusted performance (ROA and ROIC).

While consumer inertia is well documented (Heiss et al., 2021; Hortaçsu et al., 2017), the empirical literature on car insurance markets has rarely been able to separately identify whether inertia stems from inattention (failing to review offers) or from genuine switching costs and brand preferences. Previous studies (Honka, 2014; Kiss, 2019) rely on imputed choice sets or survey data, which makes this separation difficult. This thesis addresses the identification challenge of separating unobserved consumer attention from observed switching behaviour by utilising a quasi-experimental data-generating process that defines and standardises consumer choice sets and makes switching costs nearly negligible, combined with a two-stage modelling strategy.

Article I uses an EU manufacturing firm panel from Orbis Europe covering 10,190 companies in 24 countries over 2005–2018, combined with Eurostat macro indicators to measure output gaps and producer-price volatility, and applies Dynamic System-GMM to control for endogeneity and unobserved heterogeneity. Articles II and III draw on a proprietary dataset from the largest insurance broker in Estonia over 2010–2018, encompassing standardised offers from 11 insurers, observed policy choices, and detailed claims histories for car leasing customers in Estonian market where approximately 80% of new private cars are leased and insurance is mandatory. Article II employs panel Logit and Linear Probability Models with fixed effects; Article III estimates a Two-Stage Discrete Choice Model (building on Hortaçsu et al., 2017) using the method of moments, which structurally separates the probability of paying attention from the probability of switching conditional on attention.

Article I measures cyclical adversity through a value-added gap (Hodrick-Prescott filter, where adverse gaps defined as deviations greater than 3% below trend) and excess

producer-price volatility (GARCH(1,1)). Under adverse output gaps and high price volatility, higher fixed (partly irreversible) investment significantly reduces risk-adjusted ROA and ROIC, consistent with real option theory: the cost of irreversible commitment rises with adversity, making waiting the superior strategy. Working capital buffers can partly mitigate the negative impact. Non-linear thresholds are documented in the output gap, with effects reinforced when credit constraints tighten and market concentration is high.

Article II investigates consumer switching and learning in Estonian car insurance within a broker-mediated leasing channel with standardised covers. It finds that switching is strongly price-driven but asymmetric despite a baseline annual switching probability of only 11%: a 1% increase in the incumbent's renewal price raises switching probability by only 0.2 percentage points, whereas a 1% widening of the price gap relative to the cheapest available offer increases switching probability by 2 percentage points. Third-party claims increase switching probabilities, while self-induced claims reduce them. This pattern is consistent with two mechanisms: a rational adverse selection channel (at-fault consumers stay to conceal a worsened risk type), and a behavioural reciprocity channel (consumers feel loyalty after the insurer covered their own-fault accident). The data cannot distinguish between these, and both contradict the standard moral hazard prediction (Einav, 2005) of opportunistic switching.

Article III applies a two-stage structural framework to separate consumer attention to renewal offers from choice conditional on attention. The estimated probability of paying attention ranges from 18% to 26%; conditional on attention, the switching probability is approximately 30%. Brand effects are statistically significant but economically negligible, while price sensitivity in the choice stage is high: a 1% price increase reduces the likelihood of choice by 1.7%. Attention declines with and car value, but increases when past premiums have been high relative to alternatives. Robustness checks using a forced-attention subsample and a 2014 regulatory change in claim handling confirm that inertia is largely driven by rational inattention rather than switching costs or brand loyalty. Foregone consumer savings from inattention amount to approximately €3.8 million annually in the Estonian motor own-damage market – a non-trivial welfare cost in a small, transparent market and a conservative lower bound given multi-year compounding of inertia-based price drift.

The thesis contributes to the literature in several ways. The three articles collectively demonstrate that, for both companies and consumers, the dominant friction suppressing welfare-improving outcomes is not the absence of a better alternative but the cost of acting on information already available. Article I contributes broad cross-country micro-level evidence that links fixed investment timing across the business cycle to risk-adjusted financial performance (ROA and ROIC), thereby validating the investment irreversibility mechanism in terms of performance outcomes rather than investment volumes. Article II contributes by documenting an asymmetric switching response to claim type: self-induced claims reduce switching probability while third-party claims increase it. This finding is novel in the insurance switching literature and suggests that either risk concealment or reciprocity motives – rather than pure price sensitivity – mediate the switching response to at-fault-claims. Article III structurally identifies inattention as the primary driver of inertia and demonstrates that choice is rational and highly price-sensitive conditional on attention, yet overall attention remains low even in a highly standardised and transparent choice setting.

These findings carry distinct policy implications. Based on Article I, the most direct lever to decrease option value of waiting without requiring direct expenditure is reducing macroeconomic and regulatory policy uncertainty: credible multi-year fiscal frameworks, stable regulatory environments, and clear central bank forward guidance. Where uncertainty cannot be eliminated, countercyclical state-guaranteed credit schemes reduce borrowing costs when companies cannot pledge irreversible assets as collateral; these schemes should extend to working capital, preventing otherwise viable companies from depleting liquidity buffers to service irreversible assets. Policies stabilising energy and raw material prices further compress producer-price volatility, the second dimension of cyclical adversity identified in Article I. Article III identifies inattention as the dominant consumer friction. Consequently, policies that disrupt inattention — prominent display of the prior year's premium at renewal, smart defaults auto-enrolling consumers in lower-cost plans, and the Estonian 2014 reform in claim handling — are more effective than reducing switching costs or improving disclosure when consumers do not engage with disclosed information.

Lühikokkuvõte

Esseed ettevõtete otsustustest ebakindluse tingimustes ja inertsist tarbijate valikutes

Indiviidid ja ettevõtted teevad intertemporaalseid majandusotsuseid nagu investeerimisotsuseid või kindlustuse valikuid, mille eeldatavad tulemused on suurel määral ebakindlad. Neid otsuseid mõjutavad sageli turu- ja käitumuslikud tõrked, mis aeglustavad või moonutavad muutuvate majandus- ja turutingimustega kohanemist. Käesolev doktoritöö uurib selliste tõrgete kahte esinemisvormi. Esiteks seda, kuidas ettevõtete pöördumatud põhivarainvesteeringud mõjutavad nende finantstulemusi makromajandusliku ebakindluse ja krediidipiirangute tingimustes. Teiseks, kuidas tähelepanu puudus ja inerts toovad kaasa tarbijate mitteoptimaalsed autokindlustuse valikud. Töö läbivaks teemaks on, et mittetäieliku info tingimustes tegutsedes kaasnevad majandusagentidel kulud, milleks ettevõtetel on pöördumatud kulud investeeritud kapitali ja tarbijatel kognitiivne kulu uuenduspakkumistele tähelepanu pööramisel. Nende kulud põhjustavad võrreldes tõrgete puudumisega teistsuguseid tulemusi. Töö koosneb kolmest empiirilisest esseest. Artikkel I uurib Euroopa töötleva tööstuse ettevõtete investeeringuid ja tulemuslikkust läbi majandustsüklite. Artiklid II ja III aga tarbija tähelepanu, valikuid ja kindlustusandja vahetamist Eesti autokindlustusturul.

Ettevõtete investeerimisotsuseid käsitlevas varasemas kirjanduses on peamiselt uuritud, kuidas investeeringute pöördumatus ja makromajanduslik ebakindlus mõjutavad investeeringute mahtu ja ajastust (Bernanke, 1983; Dixit & Pindyck, 1994). Samas on vähe riikideüleseid mikrotasandi empiirilisi tulemusi selle kohta, kuidas pöördumatute investeeringute, võõrkapitali muutuste ja majandustsüklite vastastikmõju kandub üle riskiga korrigeeritud finantstulemustesse (*ROA ja ROIC*).

Kuigi tarbimisvalikute inertsus on kirjanduses hästi dokumenteeritud (Heiss et al., 2021; Hortaçsu et al., 2017), ei ole varasemas autokindlustust puudutavas empiirilises kirjanduses suudetud eristada, kas inerts tuleneb tähelepanu puudusest või tegelikest vahetamiskuludest ja brändieelistustest. Varasemad uuringud (Honka, 2014; Kiss, 2019) tuginevad küsitlusandmetele või tuletatud valimitele, mis raskendavad nende kahe aspekti eristamist. Käesolev doktoritöö seevastu kasutab pooleksperimentaalset andmestikku, kus tarbijatele esitatav pakkumuste valim on standardiseeritud, vaadeldav ning teenusepakkuja vahetamise rahalised kulud on tarbijatele nullilähedased. Neid andmed on sisendiks vahetamise ajendite analüüsile ning vaadeldava vahetuskäitumise ja mittevaadeldava tähelepanu eristamisele kaheetapilise modelleerimisstrateegiaga.

Artikkel I kasutab Orbis Europe'i EL-i töötleva tööstuse ettevõtete paneeli, mis hõlmab 10 190 ettevõtet 24 riigis ajavahemikul 2005–2018, kombineerituna Eurostati makromajanduslike näitajatega SKP lõhe ja tootjahindade volatiilsuse mõõtmiseks, ning rakendab dünaamilist süsteem-GMM-i endogeensuse ja mittevaadeldava heterogeensuse kontrollimiseks. Artiklid II ja III kasutavad Eesti suurima kindlustusmaakleri konfidentsiaalseid andmeid aastatest 2010–2018, mis hõlmavad 11 kindlustusandja standardiseeritud pakkumusi, tarbijate valikuid ning üksikasjalikku kahjuajalugu autoliisingu klientide kohta turul, kus ligikaudu 80% uutest autodest on liisitud ja kindlustus on kohustuslik. Artikkel II kasutab fikseeritud efektidega paneellogit- ja lineaarseid tõenäosusmudeleid; Artikkel III hindab kaheastmelist diskreetse valiku mudelit (tuginedes Hortaçsu jt, 2017) momentide meetodiga, mis eraldab struktuurselt tähelepanu pööramise tõenäosuse tingimuslikust vahetamise tõenäosusest.

Artikkel I mõõdab tsüklilist surutist SKP lõhe kaudu (Hodrick-Prescott'i filter; ebasoodne lõhe on määratletud kui negatiivne hälve trendist, mis ületab 3%) ning GARCH(1,1) mudeliga hinnatud tootjahindade ülemäärase volatiilsusega. Peamine tulemus on, et negatiivse lõhe ja kõrge hinnakõikuvuse tingimustes vähendavad suuremad (ja osaliselt pöördumatud) põhivarainvesteeringud oluliselt riskiga korrigeeritud ROA-d ja ROIC-i, mis on kooskõlas reaaloptsioonide teooriaga: pöördumatu investeerimiskohustuse kulu kasvab surutise tingimustes, muutes ootamise heaks strateegiaks. Seevastu käibekapitali puhvrid võivad seda negatiivset mõju osaliselt leevendada. SKP lõhes dokumenteeritakse mittelineaarsed lävendid, kus põhivarainvesteeringute ja majandussurutise vastastikmõju tugevneb veelgi krediidipiirangute kasvades ja turu kontsentratsiooni kõrge taseme korral.

Artikkel II uurib tarbija käitumist teenusepakkuja vahetamisel ja õppimist maakleri vahendatud, liisinglepinguga seotud autokindlustuses. Uuringus leitakse, et vahetamine on tugevalt hinnatundlik, kuid asümmeetriline. Kuigi aastane kindlustusseltsi vahetamise tõenäosus on vaid umbes 11%, siis senise teenusepakkuja uuendushinna 1% tõus suurendab vahetamise tõenäosust vaid 0,2 protsendipunkti võrra, samas kui hinnavahe suurenemine 1% võrra võrreldes odavaima saadaoleva pakkumisega suurendab vahetamise tõenäosust 2 protsendipunkti võrra. Kolmanda isiku poolt põhjustatud kahjujuhtumid suurendavad vahetamise tõenäosust, samas kui kindlustusvõtja enda süül toimunud kahjujuhtumid vähendavad seda. See muster on kooskõlas kahe mehhanismiga: ratsionaalne kahjuliku valiku kanal (süüdiolev tarbija jääb senise kindlustusseltsi juurde, et mitte avalikustada oma halvenenud riskiprofiili) ning käitumuslik vastastikkuse kanal (tarbija tunneb lojaalsust, kui kindlustusandja hüvitas tema enda põhjustatud kahju). Andmed ei võimalda neid mehhanisme eristada, kuid mõlemad on vastuolus moraaliriskile tuleneva järeldusega, et teenusepakkujat vahetatakse ennetavalt (Einav, 2005).

Artiklis III rakendatakse kaheetapilist struktuurset mudelit, mis eristab uuenduspakkumistele tähelepanu pööramist tingimuslikust valikuotsusest. Tähelepanu pööramise hinnanguline tõenäosus jääb vahemikku 18–26%; tingimuslik vahetamise tõenäosus tähelepanu pööramisel on ligikaudu 30%. Brändiefektid on statistiliselt olulised, kuid majanduslikult tähtsusetu suurusega, samas kui hinnatundlikkus valikuetapis on kõrge – hinnatõus 1% võrra vähendab valiku tõenäosust 1,7% võrra. Tähelepanu väheneb kliendisuhte pikenedes ja auto väärtuse kasvades, kuid suureneb, kui varasemad kindlustusmaksed on olnud alternatiivsete pakkumistega võrreldes kõrged. Robustsuskontrollid, mis kasutavad „sunnitud tähelepanu" alamvalimit ja 2014. aasta kahjukäsitluse regulatiivset muudatust kinnitavad, et inerts on selles turukeskkonnas suuresti tingitud ratsionaalsest tähelepanematusest, mitte vahetamisega kaasnevatest kuludest ega brändilojaalsusest. Tähelepanematusest tingitud tarbijate saamata jäänud säästud ulatuvad ligikaudu 3.8 miljoni euroni aastas ainuüksi Eesti kaskokindlustuse turul – see on märkimisväärne heaolukulu väikesel ja läbipaistval turul ning ühtlasi konservatiivne alumine piir, arvestades hinnatõusu inertsipõhist mitmeaastast kumulatiivset mõju.

Töö panustab kirjandusse mitmel viisil. Kolm artiklit näitavad ühiselt, et nii ettevõtete kui tarbijate puhul on peamine tõrge seotud juba olemasoleva teabe põhjal tegutsemise kõrge kuluga, mitte paremate alternatiivide puudumisega. Artikkel I pakub laiapõhjalist riikideülest mikrotasandi empiirilist tõendust, mis seob põhivarainvesteeringute ajastuse majandustsükli jooksul riskiga korrigeeritud finantstulemustega (ROA ja ROIC) ja kinnitab investeeringute pöördumatust nende tulemusnäitajate, mitte üksnes investeeringute mahuga. Artikkel II panustab kirjandusse käitumusliku asümmeetria dokumenteerimisega vahetusotsustes: liiklusõnnetuses süüdi olevad juhid vahetavad teenusepakkujat väiksema tõenäosusega kui süüta juhid. See leid on kirjanduses uudne ning viitab, et mitte pelgalt hinnatundlikkus, vaid ka tänutunne või siis riski varjamise motiivid mõjutavad süüdi oleva tarbija käitumist. Artikkel III tuvastab struktuurselt tähelepanematuse kui inertsi peamise tõukejõu ning näitab, et tähelepanu pööramisel on tarbija valik ratsionaalne ja tugevalt hinnatundlik, kuid üldine tähelepanu jääb madalaks isegi ülimalt standardiseeritud ja läbipaistvas turukeskkonnas.

Neil tulemustel on selged poliitikasoovitused. Artikkel I alusel on kõige peamine meede viivitusoptsiooni väärtuse vähendamiseks makromajandusliku ja regulatiivse ebakindluse vähendamine: usaldusväärsed mitmeaastased fiskaalraamistikud, stabiilne regulatiivne keskkond ja selged rahapoliitilised indikatsioonid keskpangalt. See pole ka otseselt kulukas. Kui ebakindlust ei saa kõrvaldada, siis majandussurutise ajal rakendatavad riigiabi ja laenutagatiste skeemid saavad vähendada laenamise kulusid juhul, kui pöördumatuid põhivarainvesteeringuid ei saa laenu tagatiseks kasutada. Lisaks peaksid need skeemid laienema ka käibekapitalile, sest muidu elujõulised ettevõtted ammendavad oma likviidsuspuhvrid pöördumatute põhivarade teenindamise eesmärgil. Energia- ja toorainehindu stabiliseerivad meetmed vähendavad samuti tootjahindade volatiilsust, mis on teine majandussurutise mõõdik Artikkel I-s. Tarbijaturgude puhul tuvastab Artikkel III domineeriva tõrkena tähelepanematuse. Tähelepanelikkust soodustavad meetmed on need, mis nügivad tarbijaid aktiivsemale otsingule nagu eelmise aasta kindlustusmakse esiletõstmine uuenduspakkumisel, nutikad vaikimisi valikud, mis suunavad tarbijad soodsamate pakkumuste suunas või Eesti liikluskindlustusturu 2014. aasta kahjukäsitlusreform, mis võimaldas tarbijatel pöörduda kahjukäsitluseks oma, mitte süüdlase kindlustusandja poole. Tõhusad ei ole meetmed, mis on suunatud üksnes vahetuskulude vähendamisele või info avalikustamisele juhul, kui tarbija avaldatud teabele tähelepanu ei pööra.

Appendix 1

Publication I

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RESEARCH ARTICLE

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Investment irreversibility and cyclical adversity: Implications for the financial performance of European manufacturing companies

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This investigation shows how the irreversibility constraints of fixed tangible investments conditioned on the debt flows and financial standing of a company affect its financial performance in cyclical adversity. The System General Method of Moments (GMM) estimator evaluates the endogenous link between the investment-financing flows of companies and the risk-adjusted returns on assets and invested capital. The detrimental effects on financial returns stem from the ill-fated timing of irreversible or partially irreversible fixed tangible investment and arise for companies when there is a deep cyclical gap in real value added, where this adverse effect is particularly strong under concomitant high uncertainty in producer prices.

JEL CLASSIFICATION
D81; G01; G31; G32; D92; F44

1 | INTRODUCTION

Abrupt turnarounds in aggregate demand and liquidity pose a major challenge for corporate decision-makers. Europe witnessed a drastic drop in demand and production after the 2008–2009 Global Financial Crisis and a long-lived contraction in gross capital formation. The effects of the Covid-19 crisis will only unfold over the upcoming years. Figure 1 portrays the trend in aggregate investment, real gross value added and uncertainty in the manufacturing sector over 2005–2019 for the EU-28, with uncertainty measured using both perception-based indicators and volatility indicators. Value added and gross capital formation show a steady recovery after the Global Financial Crisis and Europe's Sovereign Debt Crisis from 2013 onwards. Marschinski and Martinez Turegano (2019), however, report a loss of EU manufacturing competitiveness and a drop in global market share over 2000–2014 relative to China and other emerging economies.[1] This might explain part of the elevated and increasing uncertainty found from the World Uncertainty Index (WUI) and the European Economic Policy Uncertainty index (EPU) in the years after the crisis.[2] The estimated conditional volatility in the producer price index[3] shows a more fluctuating pattern of uncertainty, and it should be admitted that there is no unanimity on the best measure of uncertainty. Glas (2020) finds that the direct survey-based measures of expected aggregate uncertainty have a weak link with disagreement between macroeconomic forecasters shown in the European Central Bank's Survey of Professional Forecasters and that the uncertainty measures possess a smoother upward trend than the forecast disagreements, which are more volatile and stationary. They also note that survey-based measures of uncertainty correlate with overall policy uncertainty whereas disagreement between forecasters co-moves with expected fluctuations in financial markets. Given the ambiguity in the concept and measurement of aggregate uncertainty, the current study uses two distinct variables to measure cyclical adversity, considering the gap in real value added in the manufacturing sector and the conditional volatility in the producer price index, both separately and in combination. The Hodrick–Prescott filter, which separates the cyclical component from the trend growth, estimates the aggregate real value added gap for the EU in NACE-2 level manufacturing sub-sectors. The GARCH estimates of conditional variance in the aggregate producer price index for the EU in NACE-2 level manufacturing sub-sectors serve as proxies for cyclical volatility and uncertainty.

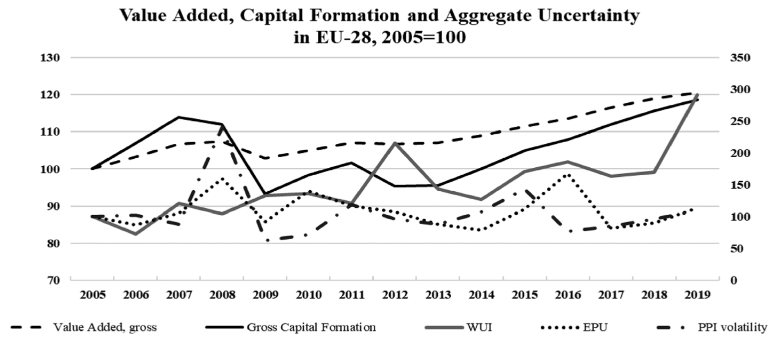

FIGURE 1 Gross value added and gross capital formation of the manufacturing sector in the EU-28 countries, 2005 = 100 (left axis), source: Eurostat (nama 10 a64, nama 10 a64 p5). World uncertainty index (WUI) 2005 = 100 (right axis), source: https://worlduncertaintyindex.com/data/; economic policy uncertainty index for Europe (EPU) 2005 = 100 (right axis), source: https://www.policyuncertainty.com/europe_monthly.html. Estimated GARCH volatility in manufacturing sector producer prices (PPI volatility), source: Eurostat (sts_inpp_m) EU-aggregate (right axis)

Investment decisions depend on expected marginal profitability of capital, which is subject to volatility and uncertainty that is particularly severe at times of aggregate economic distress. Theory on the relationship between investment and uncertainty is controversial, and whether uncertainty in output prices increases or reduces investment depends on how competitive and diversified markets are and on how flexible labour is and its share relative to capital (Abel, 1983; Caballero, 1991; Gil, 2004; Leahy & Whited, 1996). A positive relationship between investment and uncertainty was established by the theoretical models of Hartman (1972) and Abel (1983). Their models use the marginal revenue of capital, which is a convex function of output price, implying that the expected value of the marginal revenue of capital is an increasing function of uncertainty or the variance of the output price (Abel, 1983; Gil, 2004). The positive relationship between investment and uncertainty also assumes competition to be perfect and the cost of real labour to be flexible relative to capital. The empirical research has found no firm evidence for a positive link between investment and uncertainty but rather lends support to the irreversible investment argument (Bulan, 2005; Caggese, 2007; Guiso & Parigi, 1999; Leahy & Whited, 1996; Männasoo & Maripuu, 2015; Price, 1995), which suggests there is a negative relationship between investment and uncertainty as proposed by McDonald and Siegel (1986) and Dixit and Pindyck (1994). The irreversible investment argument, in line with theoretical outcomes under assumptions of imperfect competition, focuses on a trade-off choice that companies make between reaping extra returns from investing now or postponing investment under uncertainty while they gather more information about the underlying risks.

The literature on investment dynamics under financing and irreversibility constraints investigates investment choice at the microlevel (Bulan, 2005; Caggese, 2007; Guiso & Parigi, 1999) and its aggregate cyclical implications (Bernanke, 1983; Bertola & Caballero, 1994; Chen & Funke, 2010; Price, 1995, among others). The current study focuses on the micro-perspective strand of literature and investigates the dynamic endogenous mechanism between financing patterns for investment and the financial returns of a company in the face of cyclical fluctuations. The estimation of the dynamic instrumental variables unravels the investment structure, intensity and leveraging relationships to financial performance conditioned on aggregate uncertainty measured with two indicators, the cyclical deviation from the trend for real gross value added and the excess volatility in producer prices.

Adjusting or reducing capital stock is costly at times of economic distress. According to Caggese (2007), irreversibility[4] constraints prevent companies from downsizing their fixed capital if demand contracts, and this leads to reduced capital returns and profits. Corporate balance sheets becoming weaker in an economic downturn interact with the optimal capital stock, and the companies that face stronger investment irreversibility constraints are at greater peril. Caggese (2007) claims that variable working capital investments decline under concurrent financial constraints and so absorb a substantial part of the reduction in returns to fixed capital. By doing this, variable working capital investments become pro-cyclical, and this has been shown to feed into the aggregate decline in GDP in recessions (Caggese, 2007). The balance between fixed and working capital investments remaining sub-optimal may have substantial financial consequences for companies. Assuming imperfect financial markets[5] and that companies face fixed investment irreversibility constraints, Caggese (2007) finds that the capital returns over cyclical fluctuations are positively correlated with pro-cyclical fixed assets in the degree of reversibility but negatively correlated with pro-cyclical working capital investments through the degree of absorption due to binding financial constraints.

Guiso and Parigi (1999) study investment patterns under cyclical uncertainty using a repeated survey of Italian manufacturing firms and show evidence of a negative relationship between investments that are of an irreversible nature and self-reported demand uncertainty.[6] They argue that the relationship between investment decisions and uncertainty depends not only on investment irreversibility but also on several characteristics of companies, including technology, market power, investment adjustment costs and the risk aversion of the management. Xie (2009) demonstrates that greater managerial flexibility helps firms to shrink their investments during downturns in the cycle, which makes their financial returns more resilient to aggregate distress.[7] The relationships between aggregate uncertainty and investment have also been investigated by Episcopos (1995), who finds that macroeconomic uncertainty or volatility has an adverse effect on fixed private investment of a partially irreversible nature. Czarnitzki and Toole (2013) report a negative relationship between largely irreversible R&D investments and market uncertainty. Schauer (2019) documents that irreversible capital goods investments are sensitive to uncertainty for a sample of German manufacturing firms.

Chen and Funke (2010) use a three-state Markov switching regime setup to develop a stylised option-based model of investment under cyclical uncertainty. Their numerical analysis proves that macroeconomic risk and financial turmoil act as an important deterrent to investment. Caggese's (2007) model for aggregate fixed and variable capital investment includes both financial constraints and investment irreversibility and shows reinforcing mechanisms that stem from the interaction of the two types of constraint, so that financial constraints reinforce the irreversibility constraints on fixed capital investment, and the irreversibility constraints reinforce the financial constraints.

Although the dominant empirical evidence (Bulan, 2005; Czarnitzki & Toole, 2013; Episcopos, 1995; Guiso & Parigi, 1999; Schauer, 2019) shows that irreversible investments are sensitive to cyclical downturns and uncertainty, there is some limited empirical evidence for how the interaction between cyclicality and investment affects the financial returns of manufacturing companies on their assets and capital investments. This means there are not many studies that investigate the ultimate cyclical effects of investment irreversibility on the financial performance under credit constraints and limited managerial flexibility. There is also little evidence from using country-comparative dynamic microdata over the whole business cycle to investigate the endogenous effects of the investment and financing patterns of companies under aggregate fluctuations. The current study investigates the dynamics of returns on assets and invested capital from company microdata over boom and bust phases across 24 European Union member countries and 21 NACE-2 manufacturing sectors. A dynamic panel from a large sample of European manufacturing companies over 2005 to 2018 from the Orbis Europe database, formerly the Amadeus database, allows the company-level heterogeneities, state-dependencies and cycle-sensitivity patterns of companies to be controlled for. The NACE-2 level industry-country-year panel over 2005–2018 affords sufficient variation for defining our adverse shock variables. An adverse shock in real value added denotes an incidence of Hodrick-Prescott filtered deviation that is more than 3% below its trend growth value.[8] Caggese (2007) uses a similar measure to investigate procyclicality in inventory investments. Uncertainty in producer prices being above normal constitutes a GARCH conditional volatility estimate beyond the 75th upper quantile. Price (1995) employed a similar approach and proxied aggregate uncertainty with conditional variance of GDP to investigate the link between uncertainty and the investment decisions of firms. The variation in the aggregate cyclicality variables for industry sub-sector and year and the variation in financial variables for company and year allow the cycle-investment interaction effects to be identified while controlling for numerous company characteristics and aggregate country and industry-level variables. Like Caggese (2007), we look separately at variable working capital investments and irreversible or partly irreversible fixed tangible investments of companies manufacturing durable goods. The results confirm the predictions of Caggese (2007) and show that irreversibility constraints on fixed tangible investments reduce the financial returns earned by companies on total assets and invested capital. In addition, the results suggest how important competition is for financial returns and show that the density of an industry or the number of companies operating in a given sub-sector of manufacturing has a negative effect on the returns to assets and capital investment.

The remainder of the paper is organised as follows. Section 3 proposes the theoretical framework and sets out the main empirical hypothesis. Section 4 explains the data and introduces the methodological approach. Section 5 presents and discusses the results from descriptive evidence and the GMM estimations. Section 5 concludes.

2 | THE MODEL

The main hypothesis is that a company's financial returns depend on its strategic decisions about investment and financing and the effect of those decisions is driven by exogenous aggregate fluctuations arising from the macroeconomic environment (see Figure 2). How the investment and financing decisions of a given period impact the company's financial performance is also bound up with the general financial standing of the company and its managerial quality, which have shaped past decisions and past financial performance. The effect of investment and financing decisions in interaction with the aggregate economic environment has to be estimated given the company's financial and managerial standing shown in its (1) capitalisation and leverage, (2) asset structure, (3) margin and market power, (4) earnings management and (5) liquidity.

Our theoretical framework follows the dynamic, two-period investment model of Caggese (2007), but it is more closely aligned in its design with the Chen and Funke (2010) model of irreversible and partially irreversible investments under cyclical macro-economic risk. We accommodate the model from the viewpoint of the company, and so unlike that of Chen and Funke (2010), our setup does not go explicitly into the mechanisms of macroeconomic stochastic regimes but treats cyclical uncertainty as an external stochastic process that is exogenous for the company. Equally, our setup considers not only the irreversibility of investments and their adjustment costs and capital stock accumulation under cyclical uncertainty, but also the role of leveraged investments.

A company is maximising profit and choses the level of investment, which depends on a set of cost components and on the degree

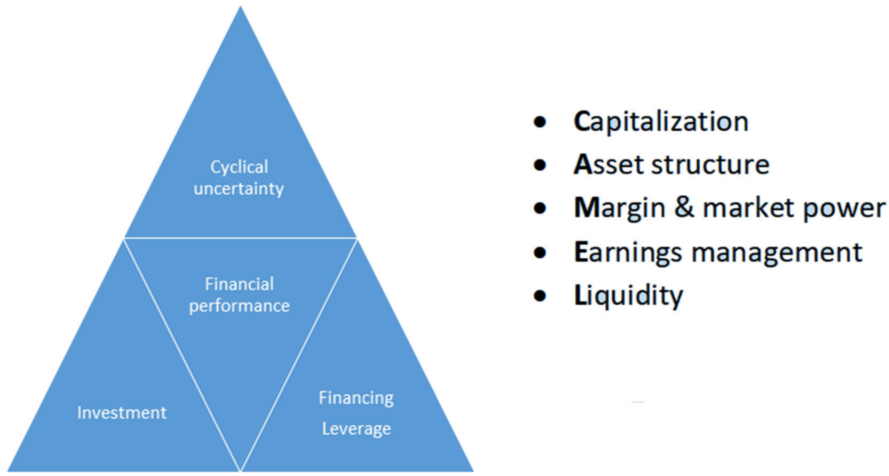

FIGURE 2 Companies' financial performance depending on investment and financing decisions and on cyclical uncertainties conditional on company financials

of perceived exogenous macroeconomic uncertainty. The investment costs are incurred in the present period, but it takes one period for that investment to become productive. The time lag in the investment returns comes from installation and adjustment, which also make the investment partly irreversible. The company maximises the profit Π from its investments (I).

$$\Pi = \max_I \left[ZK^{1-\alpha}L^{\alpha} - xK - wL - C(I) + V_s(I - \delta K - rD)\right]. \tag{1}$$

Z denotes the stochastic stationary process underlying the macroeconomic price uncertainty, a process that is exogenous to the company. The company's revenues depend on constant returns to scale, or a degree one homogeneous Cobb–Douglas production function, with capital stock K, labour endowment L and its labour share $0 < \alpha < 1$. Capital service expenses are denoted by x and wage costs by w. δ stands for the constant rate of capital depreciation. D is the leverage from past accumulated debt subject to predefined or fixed rate loan service costs r, $0 < r < 1$. V_s denotes the value of the company in two uncertainty regimes: contraction V_1 and expansion V_2, where $V_1 < V_2$. Tobin's q, which is the market value of the company's capital or assets relative to replacement cost, grows with the regime dependent company value V_s. Tobin's q is higher in expansion, which is a low uncertainty regime, and lower in contraction, or the high uncertainty regime, hence $q'(V_s) > 0$.

The costs of investment, $C(I)$, are

$$C(I) = p_k I_t + \frac{1}{2}\gamma I_t^2, \tag{2}$$

where $p_k \geq 0$ is the price per capital good unit and $1/2\gamma I_t^2$ denotes the continuous but strictly convex adjustment costs.[9]

Inserting 2 into 1, the maximisation for investment gives

$$\frac{\partial \Pi}{\partial I} = -p_k - \gamma I_t + V_s = 0 \rightarrow V_s = p_k + \gamma I_t. \tag{3}$$

This means that investments are proportional to the value of the company given the exogenous cyclicality in the macroeconomic environment. The higher the value of the company is, given macroeconomic uncertainty, the higher the positive investment adjustment costs *parameter* γ, which reflect the degree of irreversibility of investments, can be. So the more resilient the company is to an aggregate shock, the less its fixed investments are affected by irreversibility, and there is then a positive correlation between the company's fixed investments and its value reflected in pro-cyclical fixed investments.

The company has to optimise its profit by choosing the level of investment commensurate to the economic climate V_s minus the unit capital purchase costs and reciprocal to the degree of investment irreversibility reflected in the adjustment costs.

$$I_t = \frac{V_s - p_k}{\gamma}. \tag{4}$$

Augmenting the model with leveraged investments, where a company decides to finance a share θ $0 < \theta \leq 1$ with borrowed funds, the objective function for the company is

$$\Pi = \max_I \left[ZK^{1-\alpha}L^{\alpha} - xK - wL - C(I) + V_s(I - \delta K - r(D + \theta I)\right]. \tag{5}$$

The optimal level of investments is retrieved as

$$I_t = \frac{V_s(1-\theta r)-p_k}{\gamma} \rightarrow \theta r = 1 - \frac{\gamma I_t + p_k}{V_s}. \quad (6)$$

This equation shows that investments are procyclical and increasing in V_s and that the optimal level of investments decreases in debt costs r and in the share of leveraged investment θ. Rewriting this relationship shows that leverage θ grows in V_s and that it has a negative relationship with fixed assets that is proportional to the degree of irreversibility. This means that leverage has a negative relationship with fixed investments and this relationship is stronger for higher levels of irreversibility. High levels of leverage and a high degree of asset irreversibility hence imply lower fixed investment.

Given these relationships, the research hypothesis posits that there is a negative association between investment irreversibility and the financial returns at times of cyclical distress. The empirical analysis tests for the research hypotheses while controlling for the net inflows of debt and for a number of company characteristics along with country and industry-level controls.

3 | VARIABLES, SAMPLE DATA AND METHODOLOGY

3.1 | Definition of the variables

There are several measures of the financial performance of a company. Some of them, most obviously Merton's (1974) distance-to-default concept that is based on market valuation, are only applicable for listed or publicly traded companies. Alternatively, the concepts based on financial or accounting variables allow for the measurement of financial performance for a broader population of companies. The measure of financial performance used by the current study is simple and can be applied equally for listed and non-listed companies, and it resembles the *z* score used by Laeven and Levine (2009), which measures the distance to insolvency as a ratio of returns to the volatility of returns. The analysis uses two slightly varying definitions of the *z* score to measure the company's financial performance. The first definition of financial performance (FP1) divides operating profit before interest and taxes (EBIT) by the total assets and finds a ratio known as the return on assets (ROA). The second measure of financial performance (FP2) divides EBIT by invested assets, which is total assets minus current liabilities, and this gives the return on invested capital (ROIC). The volatility, or the denominator of the *z* score, is the standard deviation in returns to assets of the NACE-2 industry sector in a given year, which captures the underlying uncertainties or latent risks within the industry. The two *z*-score measures of financial performance, abbreviated as FP1 and FP2, are the two alternative dependent variables in econometric estimations.

The empirical framework estimates how the company's financial performance depends on investment and financing decisions measured as annual change in fixed tangible assets (FixedInv), current assets (CurrInv) and the annual inflow or outflow of debt (DebtFlow). In the measures for investment and financing, we do not explicitly control for the actual financing of the investments but assume implicitly (in a similar manner to Caggese, 2007) that if a company invests and does not increase its debt, this reflects internal financing. In the same vein, increasing debt together with investment implies borrowing or debt financing.

The estimation controls for a number of company-level and aggregate country-industry level varying explanatory variables. The financial fundamentals of the company evidently have a substantial compounding effect on financial performance when investment and financing decisions are made under aggregate economic fluctuations. According to the conceptual set-up (see Figure 2), the controls include five main categories of company financial fundamentals: (1) capitalisation and leverage, (2) asset structure, (3) margin and market power, (4) earnings management and (5) liquidity.

The capitalisation and leverage are measured by the equity to assets ratio (EAR). The change in current investments (CurrInv) and the log of total fixed tangible capital per employee (CapIntense) capture the asset structure. Market power is measured with the profit margin (PM). The log of past volatility in asset returns (lnROAVol) traces the company's past earnings management, whereas the cash ratio or cash to current liabilities (CashRate) ratio reflects the company's liquidity. In addition, the estimations control for the company's size as the log of the number of employees, and its age measured as the log of the number of years from incorporation until the year of observation. Sales growth is measured as the difference in log sales relative to the previous year.

The estimations control for two continuous aggregate variables on top of the country, year and industry dummies. First, the country-year varying real expenditure per capita volume index in purchasing power parity relative to the EU-28 average captures the effect of the country's income level and the maturity of the market on the financial returns of companies. Second, the number of active manufacturing enterprises populating the NACE-2 manufacturing sector in a given country controls for the effect of market density, or consolidation, on financial returns. Table 1 explains the definitions of the variables.

The cycle variable is the Hodrick–Prescott-filtered cyclical component of NACE-2 level real gross value added across the EU.[10] The aggregate real gross value added comes from Eurostat statistics on the national accounts aggregated by industry at the NACE-2 level (series nama_10_a64) in chain-linked volumes (2005), in million euros. Figure 3 below illustrates the time variation in the aggregate cycle for the companies in the estimated dataset. Figure A1 in the Appendix depicts the patterns in the alternative cycle variable, the GARCH implied volatility in producer prices.

3.2 | Data and sample

The analysis retrieves data from the Orbis Europe database (formerly Amadeus), which contains financial information on a full

TABLE 1 Descriptions and explanations of the variables

Name	Description	Source
Dependent variables: Financial performance		
$FP1 = \frac{ROA}{stdev\ ROA}$	Company inflow of funds divided by the volatility of the NACE-2 level industry sector inflow of funds in that year, where inflow of funds is measured by return on assets, ROA, which is presented in percentages and calculated as (EBIT/Total assets)*100	Orbis
$FP2 = \frac{ROIC}{stdev\ ROA}$	Company inflow of funds relative to invested funds, divided by the volatility of the NACE-2 level industry sector inflow of funds in that year. Return on invested funds, ROIC, is presented in percentages and calculated as EBIT/ (Total assets – Current liabilities)*100.	Orbis
Explanatory investment-financing decision variables		
FixedInv	Change in fixed tangible assets (excluding land, real-estate investments, and financial investments) divided by total assets [%]	Orbis
CurrInv	Change in working capital requirement divided by total assets [%]	Orbis
DebtFlow	Change in debt divided by total assets [%]	Orbis
Cycle variables		
NACE-2 sector gross value added gap	Hodrick-Prescott filtered deviation from EU-level NACE-2 industry trend growth in real gross value added. Smoothing parameter, $\lambda = 6.25$.	Eurostat
Producer price index (PPI) volatility	Uncertainty in producer prices, a GARCH(1,1) conditional volatility estimate on the EU aggregate manufacturing sector above the 75th quantile	Eurostat
Explanatory financial standing variables: Capitalisation–asset structure–market power–earnings–liquidity		
LnDSales	Difference in log of sales ln $(Sales_t)$ – ln $(Sales_{t-1})$	Orbis
EquityRatio (EAR)	Shareholder equity to total assets [%]	Orbis
CapitalIntensity	Log total tangible fixed assets per employee	Orbis
ProfitMargin	Profit generated per sales and change in inventories (EBIT/sales + Δ inventories) [%]	Orbis
CashRate	Cash ratio: Cash to current liabilities ratio [%]	Orbis
DepreciationRate	Annual depreciation or asset devaluation or revaluation rate of tangible assets [%]	Orbis
LnROAVol	Log of volatility in returns to assets over the past years (until the year t-1). Ln (standard deviation of ROA over past years).	Orbis
Explanatory variables: Company demography variables		
LnAge	Natural logarithm of age, representing years from the start of operations of the company [years]	Orbis
Size	Natural logarithm of the number of employees in the company in the past year	Orbis
Cyclicality	Co-movement of company sales and country-industry varying aggregate NACE-2 level sector sales. Past correlation between company sales (LnDSales) and log difference in aggregate industry real gross value added, ln (gross value added) $_t$ –ln (gross value added) $_{t-1}$.	Orbis Eurostat
Explanatory variables: Aggregate country and sector level variables		
IncLev	Country-year varying real expenditure per capita volume index in purchasing power parity, where EU-28 = 100	Eurostat
LnFirmCnt	Natural logarithm of the number of active manufacturing enterprises by NACE-2 level sectors in a given country from Eurostat structural business statistics.	Eurostat
Explanatory variables: Dummies		
Industry dummies	NACE-2 industry dummies	Orbis
Country dummies	Country dummies	Orbis
Year dummies	Year dummies	Orbis

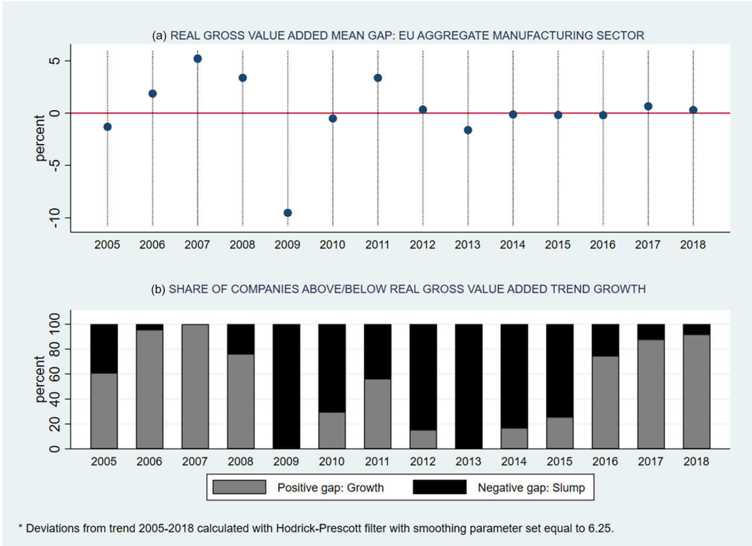

FIGURE 3 (a) Authors' calculations on Eurostat (nama_10_a64) including NACE-2 sub-sectors C10-C31. Hodrick–Prescott-filtered real gross value added mean percentage gap from trend over 2005–2018 by NACE-2 industry sub-sectors across the EU. The smoothing parameter is set to 6.25 as suggested by Ravn and Uhlig (2002). (b) Share of companies above and below real gross value added trend growth according to the Europe Orbis (Amadeus) data

TABLE 2 Summary statistics of the estimation sample with 48,608 observations and 10,190 companies

	Mean	St.Dev	Min	Max
FP1	.33	.58	−4.52	7.41
FP2	.61	1.12	−8.62	14.18
DebtFlow	−.32	10.83	−96.25	95.99
FixedInv	4.8	6.75	−61.84	95.06
CurrInv	.67	11.45	−95.43	97.01
D.LnSales	.01	.2	−2.64	3.37
ProfitMargin	4.95	6.58	−29.29	40
EquitAsset	42.55	20.81	−98.58	100
CapIntense	4.73	5.83	0	109.01
DeprRate	14.41	10	0	103.97
CashRatio	23.89	56.13	0	780.91
LnAge	3.29	.7	1.61	6.52
Employees	5.72	.98	2.3	11.03
Cyclicality	.27	.39	−1	1
Lnsd ROA past	1.26	.88	−4.81	6.15
IncLevel	104.04	19.26	43	269

Note: Authors' calculations on Europe Orbis (Amadeus) company level data by Bureau van Dijk (2020) and on Eurostat aggregate statistics. See variable definitions and data sources presented in Table 1.

population made up of manufacturing companies from 28 European Union (EU) countries with an annual turnover of more than EUR 50 million in 2005–2018. Extensive data cleaning and the process of data preparation following the guidelines of Kalemli-Ozcan, Sorensen, Villegas-Sanchez, Volosovych, and Yesiltas (2019) led to severe data anomalies being dropped, whereas only unconsolidated accounts were considered to avoid duplicating recordings of the same company data. The study limited the scope to established manufacturing companies producing durable goods[11] that had been in operation for at least 4 years and had at least 10 employees[12] and that gave an indication of ongoing business activity reflected in non-zero turnover and a positive value for total assets and invested capital, calculated as total assets net of current liabilities. Added variable plots for panel estimators, a recently developed STATA routine by Gallup (2020), identified the influential outliers in the explanatory variables from partial correlations, and the analysis consequently excluded the observations with residuals from regressions fitted on transformed variables beyond 0.5% and 99.5% at the lower and upper tails of the distribution.[13] After anomalies, extreme and influential observations were removed, and partly because of gaps in the variables, the sample for the final estimation dropped to 48,608 observations and 10,190 companies in 24 EU member countries[14] and in 21 NACE-2 industry sub-sectors.[15] The final estimation sample was missing four newer EU member countries, Croatia, Cyprus, Malta, and Lithuania, whereas the remaining 10 newer EU member states provided 1,296 companies in the final sample, or 12.7% of it. Table 2 below presents summary descriptive statistics for the estimation sample.

3.3 | The empirical model

The relationship between company financing and investment decisions and financial performance is strongly endogenous, and so using an instrumental estimator in the estimation framework is warranted. Hence, the study employs the system-generalised method of moments (GMM) estimator by Arellano and Bover (1995) and Blundell and Bond (1998) to estimate the effects of debt and investment on financial performance. The GMM panel estimator not only accounts for dynamic endogenous relationships but also controls for unobserved, time-invariant heterogeneity and state dependencies at the company level. Our dataset meets the demands of the GMM estimator for good properties as it has a large number of companies (N) and a moderate time-dimension (T). The GMM estimator assumes no residual autocorrelation after controlling for panel clusters, so we have introduced the year dummies as exogenous instruments to account for possible residual autocorrelation.

We employ robust standard errors with Windmeijer (2005) correction to avoid the downward bias in finite samples. Following Roodman (2009), we use collapsed instruments to avoid the problems of instrument proliferation, while using orthogonal deviations in setting up the instruments' matrices for reducing the attrition bias that arises because of the panel gaps. Nevertheless, the GMM results are sensitive to there being a large number of gaps in the variables that make the panel highly unbalanced.

The 1-year lagged financial performance ratio enters the model as an autoregressive endogenous term, instrumented with its own lags. The main endogenous explanatory variables of interest are the main effects of investment, and the interaction effects of fixed and current investment with the aggregate slump. The model considers all the financial variables except capital intensity as endogenous and instruments them with lagged observations. The exogenous variables in the model are the volume of country real expenditure per capita in purchasing power parity relative to the EU-28 average (IncLevel), the dummies for countries and years and the adverse industry-aggregate slump indicator (Slump). Aside from its debt inflow and investments, the financial performance of the company depends on a 1-year lagged change in log sales, the lagged profit margin, the equity-to-assets ratio, the assets depreciation ratio and the past volatility in asset returns. All these variables, together with the log of the company's age and the log of the number of employees, are considered to be endogenous to its financial performance, because the firm financial standing strongly affects the company's capital and labour resources and may alter its strategic and earnings management decisions.

$$
\begin{aligned}
FinancialPerf_{it} = {} & \alpha + \delta_t + u_i + \beta_1 FinancialPerf_{i,t-1} + \beta_2 DebtInflow_{i,t-1} \\
& + \beta_3 DebtInflow_{i,t-1} \times Slump_{jt} + \beta_4 FixedInv_{i,t-1} \\
& + \beta_5 FixedInv_{i,t-1} \times Slump_{jt} + \beta_6 CurrentInv_{i,t-1} \\
& + \beta_7 CurrentInv_{i,t-1} \times Slump_{jt} + \beta_8 D.LnSales_{i,t-1} \\
& + \beta_9 ProfitMargin_{i,t-1} + \beta_{10} EquityRatio_{i,t-1} \\
& + \beta_{11} DeprRate_{i,t-1} + \beta_{12} CashRate_{i,t-1} \\
& + \beta_{13} CapIntensity_{i,t-1} + \beta_{14} ROAVol_{i,tl-1} \\
& + \beta_{15} LnEmployees_{i,tl-1} + \beta_{16} LnAge_{i,t-1} + \beta_{17} Cyclicality_{i,t-1} \\
& + \beta_{18} IncLevel_{c,tl-1} + \beta_{19} LnIndustryDensity_{jc,tl-1} \\
& + \beta_{20} Slump_{jt} + \gamma_{1j} + \gamma_{2c} + \varepsilon_{it}
\end{aligned}
$$

α, β, δ and γ denote the coefficient estimates, where α is the constant term, the year t effects are denoted by δt, β stand for the effects measured on the explanatory variables and γ captures the dummy coefficients. ui stands for an unobserved time-invariant company i level fixed effect constrained as $\sum_{i=1}^{N} ui = 0$ or equivalently $E(u_i) = 0$, and εit is a serially uncorrelated error term. γ_{1j} denotes the NACE-2 manufacturing sub-sector level j varying dummies, and γ_{2c} denotes the country c level dummies.

4 | RESULTS

4.1 | Descriptive evidence

The main interest of the current study is in the relationship between investments and volatility adjusted financial returns or financial performance, conditional on exogenous aggregate cyclical adversities, once the company's past period performance and debt flows are controlled for. The cyclical adversity (referred to as 'Uncertainty' in Figure 4b) is a combination of a high value added gap of below 3% of the potential output level and a high level of uncertainty estimated as GARCH conditional volatility at or above the 75th percentile. Figure 4a inspects the fitted values of the second-degree polynomials of the financial performance ratio on fixed tangible investment and debt inflow on the left, and the fitted plane of the financial performance ratio (FP1) on fixed investment and current investment on the right in years of tranquillity. Figure 4b represents similar views but in years of high uncertainty and cyclical adversity.

The data plane illustrating a three-dimensional relationship between fixed investment, net debt inflow and financial performance has a dome-shaped surface at times of tranquillity (Figure 4a, left pane). Lower financial returns are associated with the tails of investment and debt distributions in an almost symmetrical manner, suggesting that both very high investment and leveraging and strong dis-investment and de-leveraging are signs of lower financial performance. The highest financial returns are associated with moderately positive investment made predominantly with internal funding. The link between fixed and current investments relative to financial returns exhibits a saddle shape at times of tranquillity (Figure 4a, right pane). Whereas extremes of high fixed capital investment and dis-investment are still associated with lower financial returns, higher current investments are related to higher financial returns in line with the proposition of Caggese (2007). He argues that profit maximisation means that current investments should exhibit procyclicality as they increase during upturns and decrease in downturns.

At times of financial uncertainty and distress, the three-dimensional relationship between financial performance, fixed investments and debt exhibits an almost flat shape, which is nearly constant along the debt inflow dimension, but is downward sloping in net fixed investment (Figure 4b, left pane). This data pattern suggests that debt inflow in cyclical adversity is neutral for financial returns, whereas the financial deterioration stems predominantly from high fixed

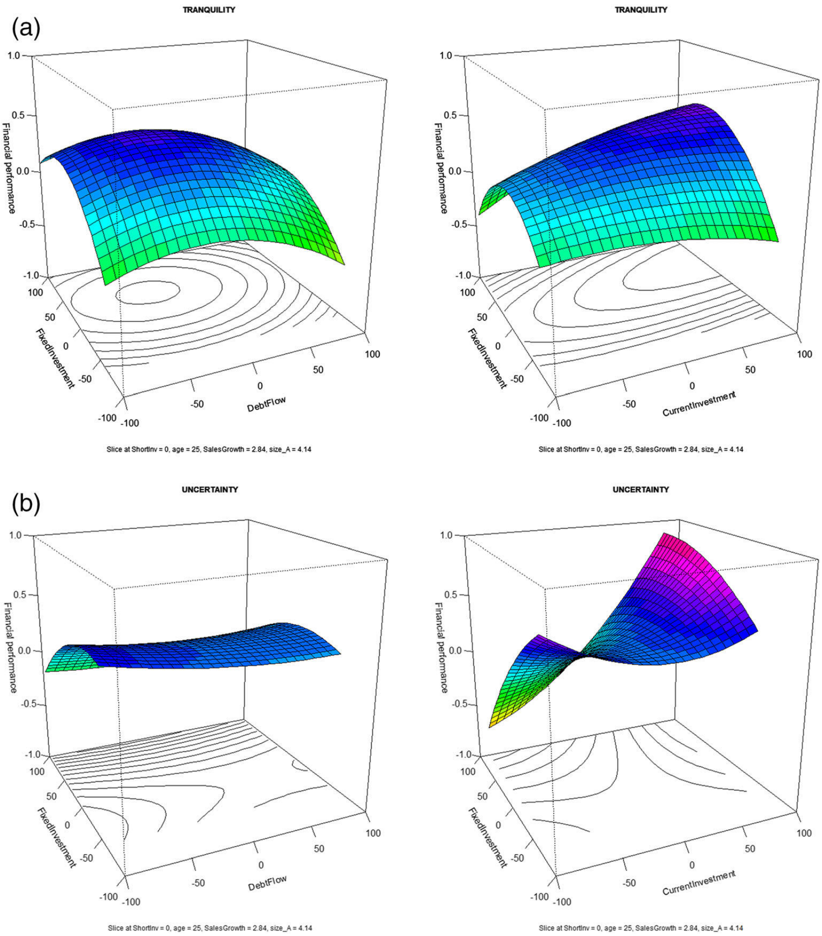

FIGURE 4 (a) Fitted values of the second-degree polynomial surfaces in years of tranquillity. Financial performance, FP1 = ROA/st.dev (ROA), on debt flow and fixed tangible investments (left), financial performance on current investments and fixed tangible investments (right). The fitted values are found at holding the company age, sales growth and size fixed at their medians. Source: Authors' calculation based on Orbis Europe (Amadeus) data. (b) Fitted values of the second-degree polynomial surfaces in years of high uncertainty. Financial performance, FP1 = ROA/stdev (ROA), on debt flow and fixed tangible investments (left); financial performance on current investments and fixed investments (right). The fitted values are found at holding the company age, sales growth and size fixed at their medians. Source: Authors' calculation based on Orbis Europe (Amadeus) data

investment, hinting at a negative effect of irreversibility of fixed assets during a cyclical downturn. The relationship of fixed and current investment to asset returns, however, has a strongly twisted shape during episodes when there is a wide output gap and high levels of uncertainty (Figure 4b, right pane). The companies that decided to maintain a higher level of current investments do significantly better, particularly those that also maintain a high level of fixed investment. Caggese (2007) points out that current investments absorb the irreversibility in fixed capital and may become inefficiently low at times of aggregate distress. In line with the proposition of Caggese (2007), the companies at greatest peril during the aggregate negative shock are those that strongly reduce their current assets while at the same time having large fixed investments that are subject to strong irreversibility constraints.

Although the surface patterns above are descriptive in nature, they largely corroborate the theoretical propositions on investment irreversibility, incomplete markets and credit frictions enforcing each other in combination. This mutual enforcement mechanism, which gains momentum in cyclical adversity, deteriorates the financial performance of companies and at the aggregate level accounts for a large part of excessively steep recessions and sluggish recoveries in the upturn phase of the cycle.

4.2 | System general method of moment estimations

System General Method of Moments (System-GMM) was used to estimate how fixed and current investments and financing affect the financial returns of companies in interaction with cyclical adversity. The estimations controlled for a number of company level and aggregate variables that are, as expected, bound together with the company's returns on total assets (FP1) and on invested capital (FP2). The system-GMM estimator also accounts for the confounding unobserved time-invariant company effect and controls for the endogeneity in the company financials. Table 3 summarises the main

TABLE 3 The GMM results on financial performance, investments and cyclical adversities, 2007–2018

	Real gross value added gap > = 3%		GARCH conditional volatility > = p75		Value added gap> = 3% high volatility > = p75	
	FP1	FP2	FP1	FP2	FP1	FP2
Investment-financing decision						
L.DebtFlow	−0.005 (0.014)	−0.015 (0.017)	−0.005 (0.011)	−0.016 (0.019)	−0.007 (0.011)	−0.019 (0.020)
L.DebtFlow*Slump	−0.015 (0.033)	−0.007 (0.035)	0.003 (0.021)	0.016 (0.023)	0.013 (0.016)	0.014 (0.044)
L.FixedInv	0.038 (0.025)	0.026 (0.025)	0.014 (0.017)	−0.019 (0.024)	0.001 (0.014)	0.025 (0.030)
L.FixedInv*Slump	−0.178*** (0.056)	−0.085 (0.069)	−0.010 (0.022)	−0.031 (0.029)	−0.180*** (0.043)	−0.263* (0.137)
L.CurrInv	−0.003 (0.017)	0.012 (0.023)	−0.020 (0.017)	0.004 (0.023)	0.013 (0.010)	0.038* (0.021)
L.CurrInv*Slump	0.069 (0.081)	0.140 (0.114)	0.039 (0.027)	0.069* (0.041)	−0.074 (0.103)	0.360 (0.288)
Financial standing						
L.FP	0.166 (0.193)	0.026 (0.073)	0.057 (0.201)	0.009 (0.056)	0.366*** (0.129)	0.043 (0.098)
LD.LnSales	0.269 (0.508)	0.152 (0.565)	0.323 (0.453)	0.800* (0.418)	0.678 (0.428)	0.098 (0.549)
L.ProfitMargin	0.001 (0.001)	0.000 (0.002)	−0.000 (0.001)	−0.001 (0.002)	0.000 (0.001)	−0.000 (0.001)
L.EquityRatio	0.002 (0.004)	0.001 (0.006)	0.001 (0.004)	0.001 (0.005)	0.005** (0.002)	0.005 (0.005)
L.CapitalIntensity	−0.006 (0.015)	−0.022 (0.036)	−0.044*** (0.017)	−0.048 (0.037)	−0.009 (0.011)	−0.001 (0.024)
L.DeprRate	0.001 (0.015)	0.006 (0.018)	0.023 (0.015)	0.009 (0.021)	−0.001 (0.010)	0.001 (0.021)
L.CashRate	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
L.LnsdROA	0.048* (0.025)	0.057* (0.030)	0.022 (0.028)	0.074** (0.032)	0.047** (0.024)	0.071* (0.039)
Company demography						
LnEmployees	−0.103 (0.138)	−0.474* (0.282)	−0.360** (0.143)	−0.626** (0.309)	−0.104 (0.104)	−0.229 (0.249)
LnAge	0.090 (0.066)	0.061 (0.052)	0.070 (0.048)	0.056 (0.052)	0.024 (0.019)	0.071 (0.049)
L.Cyclicality	−0.035 (0.041)	−0.015 (0.058)	0.002 (0.024)	−0.061** (0.029)	−0.063** (0.031)	−0.020 (0.061)
Aggregate country and sector controls						
L.IncLev	−0.004** (0.002)	−0.003 (0.003)	−0.001 (0.002)	−0.003 (0.003)	−0.003* (0.002)	−0.003 (0.004)
L.LnIndustryDensity	−0.057*** (0.015)	−0.111*** (0.020)	−0.063*** (0.019)	−0.130*** (0.019)	−0.063*** (0.013)	−0.134*** (0.026)
Slump	0.086* (0.052)	0.192** (0.084)	−0.033 (0.044)	−0.033 (0.045)	−0.019 (0.104)	0.296 (0.241)
Estimation diagnostics						
No obs	48,608	48,608	48,608	48,608	48,608	48,608
No companies	10,190	10,190	10,190	10,190	10,190	10,190
Mean obs, company	4.8	4.8	4.8	4.8	4.8	4.8
No instruments	90	105	99	111	41.05	42.01
Hansen statistic	24.84	51.48	45.82	51.58	0.19	0.51
Hansen, *p* value	0.64	0.18	0.15	0.37	−1.91	−2.60
AR1	−2.18	−3.12	−0.32	−2.69	0.06	0.01
AR1 *p* value	0.03	0.00	0.75	0.01	1.37	0.75
AR2	0.79	0.16	−0.42	−0.30	0.17	0.45
AR2 *p* value	0.43	0.87	0.67	0.77	−0.02	−0.00
AR FE	−0.02	−0.00	−0.02	−0.00	0.33	0.01
AR OLS	0.33	0.01	0.33	0.01	41.05	42.01

Note: Authors' calculations on Orbis Europe (Amadeus) data. Windmeijer (2005) finite sample corrected robust standard errors in parentheses. Coefficients for the constant term, and the year, country and NACE-2 sector dummies are not reported. L.FP OLS and L.FP FE stand for the autoregressive term in pooled OLS and fixed effects estimation to validate the System-GMM specification.

*Statistical significance at the level of 10%.

**Statistical significance at the level of 5%.

***Statistical significance at the level of 1%.

results of the estimations, and Figure 5 shows the sensitivity of the cycle interaction effects to the gap in real value added at different levels.

Table 3 presents the system-GMM results in six separate equations allowing for dual variation, both in the definition of cyclical adversity and in the definition of the outcome variable. Cyclical

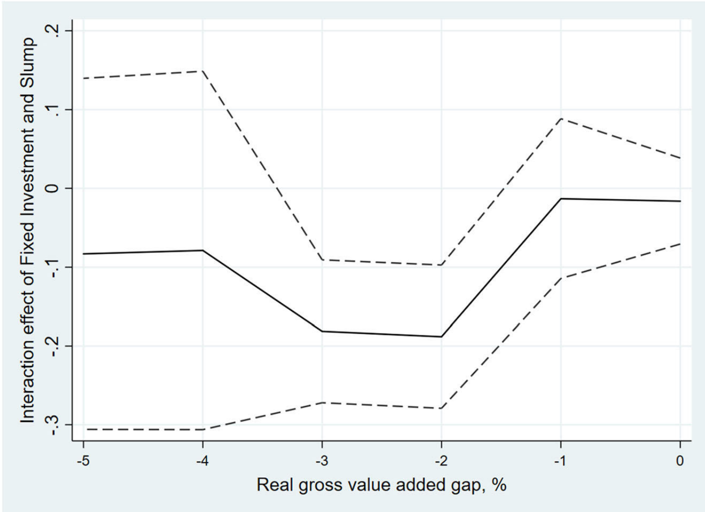

FIGURE 5 Interaction effect of 1-year lagged fixed investment net inflow with contemporaneous value of cyclical adversity. Confidence intervals at the 95% level denoted by dashed lines. Estimates were calculated with respect to FP1 = ROA/stdev (ROA) at different levels of cyclical adversity, the latter defined as the gap in real value added conditional on high volatility in producer prices (volatility beyond the 75th percentile across the observation period for a specific NACE-2 manufacturing sub-sector). Source: Author's calculations on Orbis Europe (Amadeus) and Eurostat data

adversity has three definitions: first, a gap in real gross value added that is larger than or equal to 3%; second, the conditional volatility estimated by GARCH at or beyond the 75th percentile; and finally, the combination of these definitions. Separate regressions estimated financial performance in returns on assets (FP1) and in returns to invested capital (FP2), across the three definitions of cyclical adversity.

The system-GMM panel results largely confirm the hypothesis of investment irreversibility under incomplete markets. The interaction effect of fixed investment and cyclical adversity, or a slump, is consistently negative and significant for the real value added gap and for the combined effect of a wide output gap and a high level of uncertainty in producer prices. The effect of fixed investments on financial performance is negative but insignificant with elevated uncertainty in producer prices alone (Table 3, the two middle columns). This finding corroborates the descriptive evidence (see Figure 1), which shows an inconsistent link between elevated uncertainty in producer prices and manufacturing investment. The interaction effects are more negative for the combined gap and uncertainty definition of cyclical adversity (Table 3 last two columns) than for the output gap definition alone with no consideration of uncertainty (Table 3 first two columns). This difference suggests that a negative demand shock is particularly harmful if coupled with high levels of price uncertainty, a finding that lends support to the investment literature that stresses the importance of anticipation and the adjustment aspects of fixed investment (Demers, 1991).

Figure 5 depicts the sensitivity of the interaction effect between investment and cyclical adversity, the latter defined at different levels by the gap in real gross value added. The interaction effect turns negative with a negative real value added gap, and this effect becomes statistically significant at around 1–3% below the trend growth level. Though the effect is negative, it becomes insignificant below the 4% gap and has very large standard errors. The imprecision of the estimates beyond the 4% threshold may occur because the number of episodes of extreme severity in the output gap is low and partly because of a selection bias.

The signs of the controls on the company's financial standing are mostly in agreement with expectations. The past financial returns predict higher returns in the upcoming years. Sales growth and equity ratio are associated with higher financial returns, and capital intensity with lower financial returns. The volatility in asset returns is positively linked with the mean of financial returns, tentatively hinting at a risk–return relationship. The depreciation rate, profit margin and cash rate have no definite directional relationship with financial returns when the main variables of interest are controlled for along with the other confounders.

The company demography variables control for the size and maturity of the company and for business pro-cyclicality patterns. A negative relationship between the number of employees and financial returns offers no support to the returns-to-scale hypothesis. There is a tentative positive link between company age and financial performance. The higher past co-movement (Cyclicality) of company sales with the sub-sector aggregate sales suggests lower financial returns.

The aggregate country and sector controls reflect whether the financial returns are affected by the country's income level relative to that of the EU-28, or the sub-industry density shown in the number of companies operating in the industry. The effect of the income level of the country is mostly insignificant, though there is a hint of a weak negative relationship. The industry density, however, has a consistently negative effect on the company's financial returns, suggesting that the number of companies operating in the industry suppresses the financial returns earned by each individual company.

The signs for the slump variable in isolation from the interactions with investment and financing vary. The positive relationship in two of the six equations may be surprising, but it should be noted that this coefficient carries interpretation under zero net investment and zero net debt inflow. Equally, this finding may give highly tentative support to the theory of a positive relationship between investment and uncertainty in the absence of the market frictions that underlie the irreversibility and credit constraints.

5 | CONCLUSIONS

This study investigated how investment by companies affects their financial performance in cyclical swings, a subject that has important implications for management. Financial performance was measured separately as returns on assets and returns on invested capital. The system-GMM estimations, which handle unobserved heterogeneity and endogeneity, controlled for a number of company, country and industry level variables. The evidence shows that the interaction between cyclical adversity and a company's fixed investment is negative, lending support to the investment irreversibility argument under incomplete markets. The negative investment-cyclicality effect was strongest for the aggregate slump that witnessed a concomitant gap in value added and a high level of uncertainty in producer prices. The study additionally showed that the investment irreversibility effect arises in the real value added gap in the range of 1–3% of its trend growth level. The results in combination suggest that the reinforcement mechanism operates between cyclical adversity, uncertainty and market imperfections, giving rise to the credit and investment irreversibility constraints. From the perspective of management, these findings suggest that investment decisions must be evaluated against the macroeconomic environment and volatilities and that investment may generate negative returns in the short term. Under economic uncertainties and in fear of negative returns, managers may postpone investments, and this may slow growth both at company level and at the level of the whole economy. The investment policies at company level and those of governments have to counteract forces that may unduly suppress investments and so delay economic recovery and growth.

ACKNOWLEDGMENTS

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available upon reasonable request from the corresponding author, but only conditional on the permission by Bureau van Dijk/A Moody's Analytics Company that grants licences for the use of Orbis (Europe), the underlying source of raw data for the study.

ENDNOTES

[1] Marschinski and Martinez Turegano (2019) note that although sluggish demand has been one of the main culprits in the decline in value added from manufacturing in the EU next to that in other regions, the nominal measurement against the background of cheaper industrial production, in the electronics industry in particular, has aggravated the negative trend. The loss in market share has been most evident for textiles, electronics and electrical equipment. The only manufacturing sector in the EU that has remained resilient to increasing global competition has been the pharmaceutical industry.

[2] The WUI counts the percentage frequency of the word 'uncertain' or its variants in the Economist Intelligence Unit country reports. The EPU index counts the number of newspaper articles among nine major European newspapers that contain the terms 'uncertain' or 'uncertainty', 'economic' or 'economy' and one or more policy-related terms.

[3] Estimated GARCH(1,1) conditional volatility in the aggregate producer price index for the EU manufacturing sector.

[4] Full fixed capital irreversibility is when a company has no options nor a price for resale of an asset, whereas under partial irreversibility, the company has an option to resell the assets invested for substantially below their deployment value within the firm. The implications from the study are qualitatively similar under both assumptions of full and partial investment irreversibility.

[5] Imperfect financial markets imply that options for risky borrowing or equity finance are limited or not available. For the broad literature on financial market imperfections along with the implications for aggregate investment, see Aghion, Angeletos, Banerjee, and Manova (2010), Campello (2011a and 2011b) and Buca and Vermeulen (2017) among others.

[6] The firm-level uncertainty measure employed by Guiso and Parigi (1999) was a ratio of standard deviation in the respondents' self-reported level of expected demand, or alternatively the standard deviation in the expected level of demand growth, to the stock of capital.

[7] According to Xie (2009), managerial flexibility leaves room for managers to respond to uncertainty as it increases the option value of waiting for new information and therefore enables the company to reduce the downside risks resulting from adverse market conditions.

[8] The authors have also estimated the results at the value added output gap below 1% and 2%, and both estimates gave qualitatively similar results to those with an output gap below 3%. Figure 5 illustrates the sensitivity of the investment-cycle interaction term with the value added gap at different levels. The System-GMM estimations at a value added output gap below 1% and 2% are available from the authors upon request.

[9] For the reasoning, see Chen and Funke (2010).

[10] Eurostat structural business statistics on NACE-2 level industry sales could be considered as an alternative cycle variable, but these statistics are only available for the years 2010–2017.

[11] The sample considered companies operating in sectors manufacturing durable goods in the NACE-2 classification including sub-sectors C22-C30.

[12] The European Union recommendation http://data.europa.eu/eli/reco/2003/361/oj defines enterprises with less than 10 employees as micro-enterprises. Micro-enterprises mostly have only limited access to the credit market, and their investment-credit patterns may not conform to the market, and this may distort the estimated results.

[13] Added variable plots are available from the authors upon request.

[14] AT, BE, BG, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IE, IT, LU, LV, NL, PL, PT, RO, SE, SI, SK.

[15] NACE-2 has 24 sub-sectors altogether, denoted C10-C33. The current dataset covers the NACE-2 sub-sectors C10-C30.

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APPENDIX A: UNCERTAINTY BASED ON PRODUCER PRICE GARCH ESTIMATED CONDITIONAL VOLATILITY

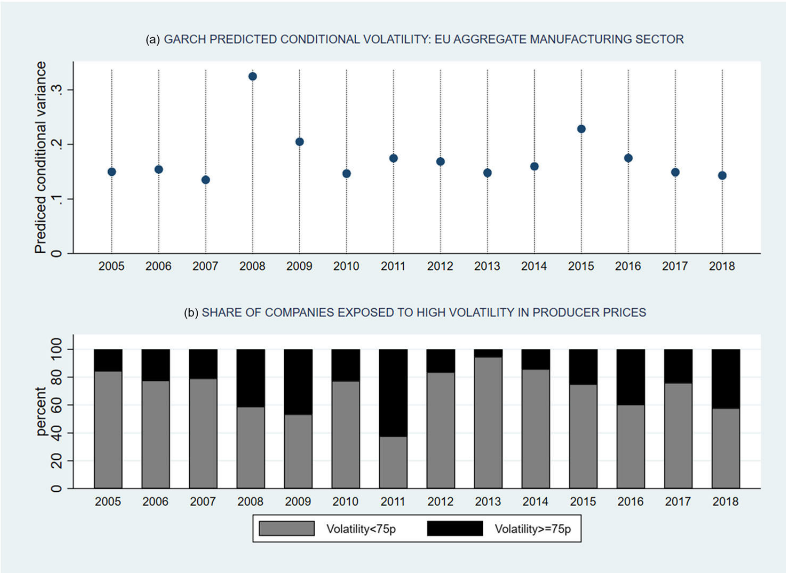

FIGURE A1 (a) Authors calculations on Eurostat producer prices (sts_inpp_m) in the manufacturing sector. GARCH estimated conditional volatilities or variances over 2005–2018. (b) Share of companies by EU-aggregate manufacturing sub-sectors exposed to high volatility at and above the highest 75th percentile according to the Europe Orbis (Amadeus)

Appendix 2

Publication II

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What drives drivers? Switching, learning, and the impact of claims in car insurance

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ABSTRACT

People rarely change their service provider, and they generally stick instead with the incumbent. This inertia is usually interpreted as market friction that is mainly due to search or switching costs, or is explained by learning about an intangible good. The actual triggers for learning are less studied, especially whether the learners' own behavior triggers the learning. We analyze field data on choices made about car insurance renewal, in which all the features offered and chosen, including claims details, are known. We follow an expected utility approach, and by controlling for individual factors we find that the decision to switch insurers is mainly driven by the direct monetary gains that result from changes within choice sets rather than changes in the default good. The learning effects are present, and, surprisingly, there is a difference in consumer behavior. Consumers at fault for a claim tend to switch significantly less than those who suffered a third-party-induced claim or made a claim with other causes.

1. Introduction

The loyalty of consumers can be observed in many different contexts. We usually go to the same hairdresser, we buy groceries from the same supermarket, and we use the same washing powder. Even though there can be a cheaper alternative of the same quality, many people carry on in the way they are used to and so lose some money.

The same is true in the insurance market. Many studies of U.S. health insurance (Abaluck & Adams-Prassl, 2021; Handel, 2013) show that people choose options that cost them more than alternatives of similar quality. Market frictions have mainly been used to explain this deviation from the rational behavior of *homo economicus*, as it is either too expensive to search for the information needed to make rational choices, or too costly to switch service provider because of the direct cost or the effort that doing so requires. Insurance is an exciting product to study because it takes time for the customer to understand their preferences or learn about the quality of the good or service on offer. This learning starts with an insured event that leads them to claim an indemnity from the insurer. Some studies use claims as a trigger for learning and switching, like Israel (2005), but we are not aware of any studies that use comprehensive datasets and investigate the causes of claims made on car insurance.

This study looks into the auto insurance market, and our interest is in the choice by car drivers to change their insurance provider. We contribute to the literature on the intertemporal consumer choice of experience goods in two ways. The first novel feature is that we study switching behavior within a single category of goods using a unique dataset from the Estonian market.

Motor insurance in Estonia is always provided under two separate policies, where Motor Third-Party Liability (MTPL) covers the damages caused to other people, and Motor Own Damage (MOD) covers the losses suffered by the insured person. The first is mandatory and fully standardized, and the consumer cannot learn from it because the claims service is not experienced by the person who bought the cover. The second policy is also standardized in our setting, but it allows the policyholder to learn from the claims service experience.

A common feature of most of the earlier studies is that the researcher cannot directly observe all of the goods and their characteristics that the

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consumer has considered. Many excellent studies use laboratory experiments or surveys or indirectly derive some features of the choice sets (Honka, 2014), though some studies use actual field data. These studies mainly consider U.S. health insurance (Abaluck & Adams-Prassl, 2021; Handel, 2013) and a few other areas like television providers (Shcherbakov, 2016), utility contracts (Hortascu et al. 2017), and pension fund management (Luco, 2019). Another feature of many earlier studies is that their data come from just one service provider, so the incentives for switching are hypothetical or unobserved.

The second novel feature of our study is that it looks at the triggers of the learning and service experience. In insurance, the consumer learns after experiencing an insured event and claiming the indemnity. The study by Israel (2005) looked at how quickly consumers learn after a claims experience and how much of their learning they incorporate into subsequent buying decisions. He used data from one insurer on the departures of consumers before and after they made car insurance claims. Our data contain the dates and explanations of claims from several insurers against a standardized cover feature set. We have sorted the claims into three categories for who caused the accident. The categories are Self-Induced for claims caused by the driver; Third-Party Induced, which includes theft, vandalism, and collisions where a third-party is at fault; and Other, which covers incidents like fire, broken windscreens, and wild animal collisions. By using claims causes we can depict the decision to switch and the learning in a novel and more precise way.

Our method was to exploit a setting where consumers make a forced choice between standardized alternatives when they enter the first insurance contract in year one, and then they are presented with the same choice with all the other options again the next year. However, if the consumer is satisfied with their previous choice or ignores the renewal option, the contract will continue with the same service provider that they had in the previous year. In contrast to other consumer switching studies, we observe actual choice sets of prices and product features offered, and the choices made over five years. We do not need to impute any significant inputs.

Our setting does not involve any direct monetary costs for search or switching. Our data cover insurance contracts for leased cars and the leasing company prescribes what cover is needed, so there is no need to search for the right cover. In addition, the panel of choices on offer that is presented to the customer includes most of the options available in the market. The potential outside good for the whole consideration set is unlikely to be better in its cover or premiums than the policies in the choice set. The frequency of choice is exogenous, so we need not address the endogeneity of the timing of decisions. The primary data come from the largest insurance broker in Estonia and include pricing data on all the offers made, the actual choices and claims.

We set up an econometric model of choice that describes the likelihood of the consumer switching insurance provider and captures different triggers for switching and their magnitudes, together with product characteristics like prices, the brand preference for the customer's given insurer, and demographic characteristics. It also captures claims, and controls for customer preferences towards a particular insurer to see the learning effects from one period to another. We use the number and monetary value of the claims and all the details about their causes.

We estimate the model using individual-level choice data in an unbalanced panel covering the full years 2012-2017, and find that inertia plays a significant role in this choice context. We can separate previously tested determinants like age, gender and product characteristics, and add different triggers for learning about product quality in the form of switching triggers. As expected, changes in pricing play a significant role. When the incumbent increases its prices by 1% from the year before, the likelihood of switching increases by 0.2 percentage point, whereas a price difference of 1% between the offer of the incumbent insurer and the cheapest alternative available increases the probability of switching by 2 percentage points from the base value. In most of the models estimated, we show that if the consumer merely experiences any type of claim, it has no impact on switching and learning. Once we control for specific claim types, we see that consumers are less likely to switch when they are at fault. Their propensity to switch increases when a third party was the reason for the claim, but not with the other reasons for an accident, hinting at a behavioral implication of our study.

The rest of the paper proceeds as follows. We begin by giving an overview of the related literature in Section 2. Section 3 describes the data and the choice context that creates the data for our research. Section 4 introduces the model used. Section 5 continues with the estimation results and discussion, Section 6 contains robustness checks, and Section 7 concludes.

2. Previous literature on consumer switching

Neoclassical economic theory posits that consumers are homo economicus, meaning they maximize their utility, and they use all the information available in doing so. Consumers are also assumed to process that information appropriately, and their preferences are assumed to be time-consistent and affected only by their payoffs and not by the decision frames.

The validity of these assumptions has been studied extensively, especially in behavioral and experimental economics. A common feature in the research has been to establish that there is inertia in updating choices over time. The literature on applied economics has in the past decade documented significant default effects (DellaVigna, 2009). Consumers often do not search for better options, meaning they do not use all of the available information or do not seek information in order to make a new choice from time to time. Moreover, even if the information is available, they do not process it correctly in a way that would let them choose better options. They stick with their previous decision rather than deciding anew and switching when new information arrives.

Consumer inertia as a deviation from rational behavior has mainly been explained by two types of market friction. The first is the cost of searching for the optimal solution, which was described in a seminal article by Stigler (1961). This idea is that the information needed is not readily available and it takes time to search for it, which has an opportunity cost. The second type of friction is related to switching, as there may be direct or indirect costs from switching the current service provider. These approaches mean that seemingly non-optimal behavior can be rationalized by the adjustment cost from search and switching costs.

Early studies in this field like Berger et al. (1989) focus on either search or switching costs. Some subsequent studies such as Schlesinger and Schulenburg (1993) examine both types of cost in decisions to switch car insurers using surveys and various parameters for insurer quality or develop implications on competition and welfare like Wilson (2012). Einav et al. (2010) describe switching decisions in the car insurance context and find that the inertia explained by market frictions is substantial. They also stress the need to have individual-level data when studying general insurance choices, because contract terms and prices are highly customized for each consumer.

Individual-level data have mainly been used to study consumer switching in health insurance markets. Handel (2013) tries to quantify inertia in health insurance choices in the U.S. and finds that it causes $2000 of financial loss per year on average relative to the optimal solution in employer-sponsored health insurance. The study by Ho et al.

(2017) has an annual savings estimate in Medicare D choices of around $1050 for the average consumer. They identify this from the variation in the data on actual choices. Many other studies document choice inefficiencies and inertia in health insurance (Abaluck & Adams-Prassl, 2021; Bhargava et al., 2017, and Ho et al., 2017) and recent attempts have been made to separate inattention to the choice from switching costs, like Heiss et al. (2021).

Outside of the United States, Boonen et al. (2016) examine the propensity to switch based on the price to consumers, service quality, and information search in the competitive Dutch health insurance market. They find that the switching propensity depends negatively on the quality of insurance contracts, positively on price and education, and negatively on age. Searching increases the propensity to switch. There are also studies on pure behavioral aspects of switching like Schmitz and Ziebarth (2017), who consider the willingness to switch depending on how the switching decision is framed.

There are fewer studies that use field data to study insurance types other than health insurance. Honka (2014) estimates the costs of both search and switching for car insurance in the U.S., but she does not incorporate learning effects. She finds that the average switching cost is around $40 per consumer, with the cost of the search ranging from $35 over the internet to $170 when a local agent is used. Unlike our study, she used comprehensive consumer survey data and pricing data to reconstruct implied choice sets in order to estimate the magnitude of the search and switching costs. Her dataset contained fewer than 1000 consumers. Kiss (2019) uses data on the Hungarian insurance market for Motor Third Party Liability, finding the search and switching cost to be between €60 and €110 per policy, and uses general pricing sheets to recover the implied choice sets for individual choices.

Sims (2003) proposes that individuals have limited capacity for processing information, which is an approach that is closely related to the adjustment cost explanation. In this case, it might be rational for consumers not to spend much time trying to understand different choices if they believe their choices would ultimately remain the same.

One particular type of information processing argument appears in the learning literature (or Evans et al., 2001, Sargent, 1993 for example). Learning has a specific form with insurance, since insurance is an intangible good. Only when an indemnity is claimed does the consumer experience the quality of the product, especially if the products are otherwise of sufficient quality and meet expectations. Israel (2005) studies learning using the departure decisions of consumers. He estimates a learning model and lock-in from the data from one insurer and uses market averages to aggregate other offers. We depart from this setup by adding the attributes of competing offers and new choices. Switching has also been studied from field data in the context of moral hazard (Liu et al., 2020).

Osborne (2011) incorporates both learning and switching costs for a packaged consumer good that is bought frequently. He finds that both learning effects and switching costs are present and that consumers learn about their tastes by purchasing new products. He also argues that leaving out one or the other effect may lead to significant biases.

Miravete and Palacios-Huerta (2014) study consumer switching decisions in a U.S. local phone market. In doing so, they distinguish between two effects, which are the impact of past endogenous experience and learning, and the impact of pure inertia. They conclude that consumers can learn from bad choices and make better decisions in the next period. In subsequent work, Hortaçsu et al. (2017) look at switching decisions in the Texas residential electricity market using monthly consumption data for households. They estimate a two-stage discrete choice model to separate inattention to decisions from brand and other preferences, and they conclude that people consider switching their service supplier once every 4-5 years.

3. Data and context

3.1. Institutional and choice context

The Estonian motor insurance market has some specific features that should be borne in mind when interpreting the setup of our study in a broader international context. Like those in several other Central and Eastern European countries, customers in Estonia usually buy two motor policies for their cars. Having an MTPL policy is mandatory, and every vehicle driven on public roads has to have this cover. The MOD policy is optional, and a lot of car owners choose to buy it, more often for newer cars and always for leased ones. The older a vehicle gets, the less likely it is to have a Motor Own Damage policy, except in the case of leased cars, where leasing companies set it as a requirement. Our interest in studying learning effects means that we only use Motor Own Damage policies.

The Motor Insurance Bureau collects all statistics on claims made under MTPL insurance, which is the most common type of car insurance and is compulsory. Each insurer can use information on all previous claims in their MTPL pricing. However, there is no central database for MOD claims and no market-wide no claims bonus for MOD policies. When an MOD policy is signed, no insurer asked for any previous claims history during our sample period. Some insurers use information on MTPL claims as one of the pricing inputs, but there is no generally accepted best practice for doing this, and even if there is, it only covers the damage caused to other vehicles, not the damage done to the customer's car.

The decisions made by the consumers in the dataset represent insurance choices related to around 30% of the total volume of leases issued in Estonia in 2012-2017. Leasing companies require lessees to have two types of cover for their leased cars, with the Motor Third Party Liability that is compulsory by law, and Motor Own Damage, where the leasing company sets the minimum cover level. This means that all leasing customers must have comprehensive motor cover, which Motor Own Damage is part of, with standardized features set by the leasing company. They can buy cover from different insurers and can buy their insurance policies on a stand-alone basis or through the insurance broker who works for the leasing company.

The leasing companies set the following minimum requirements for cover, which have been stable over the period we observe:

- the cover is comprehensive cover, or the perils named in it must be: fire, earthquake, explosion, theft, vandalism, windshield, collision with animals, any damage, and loss of the car;
- the insured value must at all times correspond to the amount outstanding under the lease payment schedule
- all damage must be repaired, except in cases of total loss or theft. For all cars that are less than four years old, only original, category A, spare parts may be used for repairs, and these cars must be repaired at the official dealer workshops if the customer demands. B-category spare parts are also allowed for vehicles that are four years old and older, and the repairs do not have to be done at the official dealer workshops;
- the level of deductibles must be either €200 or €300, with some minimal variation allowed, for repairs, and the deductible for theft or total loss can be a maximum of 15% of the insured value.

If a lessee buys motor insurance through the leasing company using the broker, the broker sends a standardized quote request electronically to almost all the insurers operating in the Estonian market. The quote request contains the same list of perils to be insured with equal pricing inputs for all insurers, and quotes are requested for two standardized deductible levels of €200 and €300. The broker combines these quotes into a panel of choices with the prices from each insurance company for each deductible level. This is sent to the customer alongside the lease offer. After the customer indicates which their preferred insurer is, an insurance certificate is issued. Consumers can equally buy their insurance by applying their own preferences, for a certain brand that is not presented in the panel for example, or by using a discount from a direct online purchase from some insurers. However, most consumers choose to buy insurance from the leasing company and have it managed within the overall leasing arrangement.

The set of choices contains almost all the goods that the consumer can consider, and the insurance companies represented in the panel have a total market share of more than 90%. The leasing companies additionally require all insurers to match the price offered in the leasing insurance panel if they decide to sell the same product through a different sales channel. This means the price of a potential outside good in the choice set cannot be any different to that in the consideration set.

All insurance policies are signed for one year and renewed yearly for the whole duration of the underlying leasing contract. After the first year, the consumer chooses again from the standardized competing offers of different insurers. Consumers are free to stay with their current insurer or switch to another. At the same time, insurers are free to change the price at renewal in response to their claims experience with the customer or for any other commercial reasons. Their choices in this can be tracked.

3.2. Data

We use data from multiple sources. The first source is one of the largest insurance brokers in Estonia, which serves and administers insurance policies for the big car leasing companies. A lease is the most common way of buying a new car in Estonia, and some 80% of all cars newly sold in Estonia in the period observed were leased. Leases are a common substitute for car loans. The data on insurance offers and policies cover the years 2011-2017 and have been combined and anonymized by the broker. We can directly observe all the insurance offers made to customers, including prices and insurance coverage features like deductibles and the perils insured, though the list of perils is standardized. We also observe choices of customers and demographic factors like age and gender, and we use the car data as a proxy for consumer preferences. As our study focuses on switching by consumers, we have excluded all commercial customers from the dataset.

The second data source is insurance claims for all policies in 2012-2017 and their match to policies, with both datasets coming from the same broker. Making a claim might affect the decision to switch as the customer learns directly from the good or bad service they receive when the claim is handled. Switching might equally be impacted by the pricing decision of the incumbent insurer for the next period. We expect the likelihood of switching to be higher if the incumbent insurer raises the price.

We have also gathered a third set of data on the reputations of insurers. It is plausible to assume that each one may have a specific reputation for claims handling and that consumers might consider this when they make their purchase decisions. The data come from the Estonian Insurance Association, which has an ombudsman body that resolves customer disputes with insurers. The reputation variable is the relative reputation against the average market reputation in a given year. The reputation itself measures the number of customer disputes against the number of customers, and it is interpreted that a higher value indicates a weaker reputation.

Combining these datasets gives us an estimation sample that is an unbalanced panel covering data for the full years of 2012-2017. As we only study renewal decisions, 2012 is used for earlier policies that have come up for renewal, and for which we have complete claims records for the previous years.

Two features make the dataset unique. The first is that the insurance offer made together with the leasing offer contains a panel of choices offered by different insurers, with the leasing company standardizing the cover provided in these offers and the deductible levels. This means the choice set is standardized and there is no self-selection bias towards a particular insurer, as might be the case if the study only used data from one insurer. It also means that there is no need to search for information before making the choice as all the offers will comply with the requirements of the leasing company. The second feature is that the offers are highly comparable. The standardization of the cover provided, with the same list of perils and standardized deductibles in each offer, means the offers are essentially the same, with only the prices differing. There might be some slight variation in cover features offered above the minimum, but there is minimal incentive for the insurer to offer those since they may raise the price for the customer and make the offer less attractive than those of competitors.

To give a standardized sample, we have only included customers that take out insurance with a deductible of around €200, and we have omitted all other choices. For the sake of clarity, the customer can switch from a higher deductible to a lower one and the other way. However, no customers in our sample did this during the period observed, and the overwhelming majority of more than 96% of the customers opted for the

Table 1
Summary statistics of the sample.

Variable	Mean	St. dev.	Min	Max
The probability of switching	0.11	0.31	0	1
The probability of switching conditional on no claims	0.10	0.30	0	1
The probability of switching conditional on at least one claim	0.13	0.34	0	1
Consumer characteristics				
Gender (= 1 if the policyholder is male and 0 otherwise)	0.62	0.48	0	1
Age, years	44.72	10.93	20	82
Engine power, in MW	0.09	0.02	0	0.37
Car value, in € 1000	14.43	7.65	0	388.78
Car age, years	3.71	2.28	1	12
Product characteristics				
Actual policy price, in €	393.78	147.13	116.87	3191.25
The relative price change of incumbent insurer at renewal, in %	-2.63	12.18	-73.55	579.75
The relative difference between the incumbent and minimum price offered, in %	8.12	16.39	0	926.14
The relative difference between incumbent insurer offer and mean price offered, in %	-13.15	12.69	-90.25	253.45
Service provider reputation relative to the sector's mean reputation in a given year	-0.15	0.83	-0.98	7.08
The proportion of consumers who actively search for an insurer	0.01	0.12	0	1
The proportion of policies with at least one claim per year	0.20	0.40	0	1
Total claim amount per year, in €	1154.91	1516.35	0	27378.27
The probability of switching by claim type				
Self-Induced claims	0.08	0.27	0	1
Third-Party Induced	0.17	0.38	0	1
Other claims	0.09	0.29	0	1
The number of consumers observed	20,759			
Number of observations	50,553			

Notes: A more comprehensive description of the variables is provided in Appendix 1. Service provider reputation is measured as the share of each insurer's disputes with customers relative to its market share. Self-Induced claims are defined as claims induced by the driver. Third-Party Induced claims are defined as theft, vandalism, and collisions at third-party fault. Other claims are defined as fire, broken windscreens, wild animal collision, breakdown, and all other reasons.

lower deductible level.

Table 1 provides summary statistics for the data available. The definitions of the variables are given in Appendix 1. The first observation from Table 1 is that only about 11% of consumers on average switch their insurance provider in any given year. The probability of switching fluctuates between 7% and 15% over the years, without any trend. The average probability of a switch is 10% if there were no claims during the year, and the probability of switching is 13% if at least one claim was made. It seems that customers who experience a claim tend to switch more often.

Our dataset contains slightly more males than females, and the average age of a customer is 45. We will look at the issues of potential multicollinearity between explanatory variables when developing the model. A more detailed view can be found in Appendix 2, which provides the correlation matrix of the variables.

The average price paid for a Motor Own Damage contract is €394. There is significant variation between the prices offered, and the consumer does not always choose the cheapest option. We have split the price changes into two parts. We start with what the incumbent insurer offers in comparison to what they offered in the previous year. Table 1 shows that the average price for the same consumer fell by 2.6% or approximately €10 if the consumer stayed with their current, incumbent insurer. The second price element is the difference between this price and the cheapest other option available.

Although the incumbent insurer cuts their price from the previous year on average, more affordable options are still available. The average price difference between the incumbent's offer and the cheapest offer is 8.1%, or approximately €32. The incumbent's offer meanwhile is 13.2% or €53 cheaper than the mean price offered in the panel.

The relative reputation of the service provider has a mean value of -0.15 because of the variable's construction. However, the distribution of this variable is skewed towards a couple of insurers that have a relatively large number of disputes relative to the market, while some other insurers have very few. The variable having a positive sign indicates relatively more disputes and a worse reputation than the average.

Only 1.45% of the customers told the leasing company that they would take care of their insurance for themselves and present policies that comply with the requirements of the leasing company every year. These customers have been labeled "Active" in our study. This label is also used for those who have consented to receive the offers from the full panel of different choices and chosen their cover from an insurer presented in the panel. This might be an indication of a very attentive consumer.

Claims can act as triggers or accelerators for learning about the actual quality of service. We use data on the number of claims and their monetary value, and detailed descriptions of each of them. Around 20% of the policies have at least one claim per year, and the average value of the claims was €1155 per year. As there is no established market standard for categorizing claims, we sorted all the claims into three categories from their descriptions.

If a Third Party caused the claim, the consumer could not have avoided the incident that provoked the claim. The second claims category with a dummy for Self-Induced claims means that the customer's behavior caused the claim. This category covers incidents when the insured driver is at fault, like hitting other cars, driving off the road, or hitting other objects. The behavioral implications that impact Self-Induced claims may be different to those affecting the last category. We group other causes of claims where the trigger is neither the driver nor a third party and is primarily natural, such as fire, collision with wild animals, mechanical breakdown, and glass claims, into a third category as a baseline case labeled Other Claims.

Table 1 shows that the probability of switching in the sample is significantly higher if the claim was triggered by a third party than it is with other causes. In our sample, 17% of customers whose cars were damaged by a third party switch their insurer, while 8% of those with self-induced claims do so, and 9% of those whose claims have other causes.

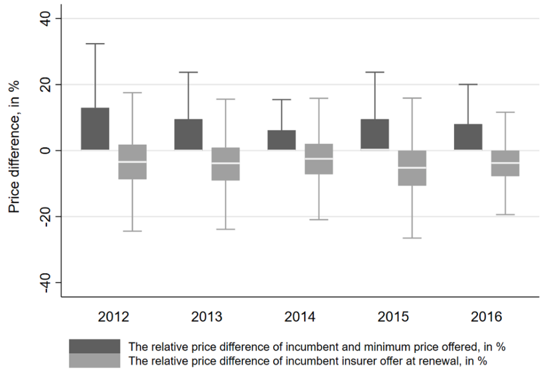

Fig. 1. Box plot of the time dynamics of relative price difference variables, 2012-2016.

There is only a slight variation in the relative price differences over time, as can be seen in Fig. 1. In our sample, the incumbent insurer's price at renewal falls each year because of the institutional setting where the renewal offers are put into a new decision context every year. All the insurers are competing for the same customers again at each renewal. They cannot afford to use dual pricing for new entrants and existing customers, where the renewal price starts to increase afterward. In around 50% of the cases in our dataset, it turns out that the incumbent actually offers the lowest price. There is also a difference against the minimum price for each year, which might indicate customer preferences for a specific insurer or real default inertia that we try to disentangle later.

4. Modeling and identification

Before describing the model, it is essential to emphasize the choice context described in Section 3.1. All customers need to buy an insurance policy because of the requirements set by the leasing company. These requirements mean they do not need to decide which cover they want to buy. This is standardized, and all the insurers are quoting the same parameters in response to the broker's request. The broker combines all the quotes into a standardized panel of different offers to satisfy the leasing company's requirements for the features of the cover. This means there is only a limited reason to search for information as the customers are presented with offers from 90% of the insurance providers in the total market. Insurers in the panel can have no monetary incentive for giving a better price for the reasons explained earlier.

As explained in the previous section, only a tiny fraction of customers, whom we have labeled "active", decide not to use the broker's services and opt to buy a policy themselves. We have also used this feature in the robustness checks as it may be a proxy for eagerness to search. This might give an indication of customer preferences that are not controlled for with the other variables we use.

Since the leasing company sets the search criteria for the coverage needed and the prices, and other observable outside offers cannot be different from the offers made in the broker panel except in their brand

and some limited exceptions that are not priced separately by insurers,[1] we can assume that the search and choice can be modeled simultaneously. In assuming this, we follow Honka and Chintagunta (2017).

Many previous studies like Handel and Kolstad (2015) or Honka (2014) have used the random utility approach. Our setting results in a simplified logistic approach because of the institutional setting explained in Section 3.1. In our case, consumer i can either stay with the current insurer j within period t by obtaining utility U_{ijt}, or can switch insurer to j' and obtain a different utility $U_{ij't}$. The consumer switches their current insurer for a new one whenever $U_{ij't} > U_{ijt}$.

The utility gain from switching is modeled as the difference between these two utilities $U^*_{it} = U_{ij't} - U_{ijt} = \boldsymbol{X}'\boldsymbol{\beta}_i + \boldsymbol{Y}'\boldsymbol{\beta}_{it} + \boldsymbol{Z}'\boldsymbol{\beta}_{it} + \varepsilon_{it}$.

Vector $\boldsymbol{X}$ contains consumer characteristics, vector $\boldsymbol{Y}$ contains the utility attributes of the products, and vector $\boldsymbol{Z}$ contains effects from learning about the insurance provider's service over time, which is triggered by claims. We will explain the variables in more detail below. The random terms ε_{it} represent elements that are known to the customer, but which the researcher cannot observe.

It seems appropriate to take a simplified logistic approach to investigating switching behavior that follows both Boonen (2016) and Kiss (2019). We aim to estimate the probability of the customer switching insurer, where the dependent variable is the decision to switch insurer at renewal. Switching means having a different insurer in period t to that in period t-1. In the logistic approach, this will be

$$Pr_{it}(switch = 1) = \frac{exp(\beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{Y}_{i,t} + \beta_3 \boldsymbol{Z}_{i,t})}{1 + exp(\beta_1 \boldsymbol{X}_{i,t} + \beta_2 \boldsymbol{Y}_{i,t} + \beta_3 \boldsymbol{Z}_{i,t})}$$

Like Honka (2014), we include different sets of variables. In order to control for any observable heterogeneity in consumer characteristics that may explain switching, the vector $\boldsymbol{X}_i$ contains factors like age and gender. As we have a setting where cars are leased and the value of the car is transformed into a monthly installment, we use car value or car age as a proxy for consumer income. Appendix 2 shows that car age and car value are correlated with each other. We also use engine power as a proxy for consumer preferences.

The vector $\boldsymbol{Y}_{i,t}$ contains observable product characteristics such as direct monetary gains from switching, and controls for consumer preferences with dummies for the insurer and the make of car, and the engine power of the leased car. Following Handel and Kolstad (2015) among others, the differences in price between the different options play a significant role as a driver for switching. As explained in the previous section, we have divided the potential gain into two parts.

The incumbent insurer can change the price at each renewal, and it is on average 2.6% lower in year t than in the previous year t-1, but there was significant variation within this. The variable is "The relative price change of the incumbent insurer".

There is potential endogeneity in pricing because the incumbent's renewal price may depend on claims made in previous periods by customers, and the incumbent insurer uses its own experience from the claims in its pricing. To control for the effect of the incumbent insurer's renewal offer price changing as a result of a claim, we interact the claim type and the difference in the incumbent insurer's price in some specifications. This helps to separate out the monetary effect of experience pricing from other monetary incentives.

We also include the relative price difference between the incumbent's offer at renewal time t and the minimum price in the choice set at the same renewal. It is reasonable to assume that this price difference plays a role in switching. The other benefit of dividing the potential impact of pricing on the switching decision into two parts is that it can ascertain whether there is a difference between the total monetary gain and the different elements that may depend on the monetary gain or loss resulting from a claim with the incumbent insurer.

Many price differences turn out to be zero, especially the difference between the incumbent renewal offer and the cheapest offer. About a third of the incumbent offers in our dataset were the cheapest offer made, as also depicted in Fig. 1. To capture the maximum amount of information for the estimation and so as not to lose the observations where the price was no different to either the incumbent's price from the previous year or to the minimum price offered, we use the inverse hyperbolic sine (IHS) transformation[2] for price differences, as IHS is defined for zero differences. It can be interpreted similarly to log transformations, as explained in Burbidge et al. (1988).

We also want to control for insurer brand preferences. We proxy this by the length of the relationship in years since the first contract for a given car between the incumbent insurer and the given owner.

The vector $\boldsymbol{Z}_{i,t}$ contains variables that describe the learning effect. To examine the learning effects for insurance as an intangible good following Israel (2005), we add a dummy for having at least one claim during the period before renewal. We later replace this general claim dummy with dummies for different claims categories in order to capture potential behavioral drivers in some specifications. We also want to control for two different effects on learning. The first is the indirect word-of-mouth and publicly available information that the consumer may use without having experienced the service after an accident. We control for this by adding the reputation indicator we constructed from the number of customer disputes for the insurer relative to its market share. This variable enters the model with a lag. As explained earlier, we want to separate out learning effects that result from a claim, and so we interact the lagged claims with the price differences of the incumbent. Finally, $\varepsilon_{i,t}$ captures the unobservable elements of utility, and for later modeling, $\varepsilon_{i,t}$ is assumed to follow Extreme Value Type I distribution.

Before proceeding, we want to understand the potential multicollinearity between the different factors. The correlation coefficients are provided in Appendix 2. The only notable correlation coefficients are between car age and car value, which are negative as would be expected, and between car value and engine power, which have a positive sign. This is also expected as more powerful cars are usually more expensive.

We use a panel logit regression with random effects in the estimation, as we want to estimate gender and some proxies for preferences that are time-invariant, like engine power and brand dummies for make of car or insurer. The specification choice for a panel with random effects was validated with the Hausman test. We also use a linear probability model with fixed effects to separate individual preference effects from those already mentioned. Many customers do not have any claims during the estimation period, and many variables of interest are time-invariant. As a result, we would lose a lot of information if we used the fixed-effects model, as it cannot capture the effect of time-invariant variables. Therefore the linear probability model with fixed effects is the main model used to validate the main findings.

5. Results

We analyze several specifications that contain consumer characteristics, the utility attributes of the products, and indicators for learning. We add the event of a claim in the previous period as a dummy or use the monetary value of a claim instead. We later explore the role that

[1] As there is electronic quoting, all the insurers respond to the same set of parameters that are used for pricing. However, some insurers might decide to include extra features in their cover for which pricing input parameters are not required, and which are consequently not priced separately. This feature might eventually create additional heterogeneity that is not reflected in the prices we observe but that may be salient to the customer if they work carefully through the wordings of all the competing offers.

[2] The variable will be transformed as $\text{arcsinh}(x) = \ln(x + \sqrt{x^2+1})\langle/END\rangle$.

Table 2
Switching probabilities in baseline models, marginal effects (except the last column).

VARIABLES	(1) Consumer characteristics and incumbent price change	(2) Consumer characteristics and the price difference to minimum offer	(3) Consumer characteristics and both price differences	(4) Model (3) + sum of claims	(5FX) Consumer characteristics, price differences, consumer FX
Gender (Male=1)	-0.002	-0.001	-0.001	-0.001	
	(0.003)	(0.003)	(0.003)	(0.003)	
Age, in years	-0.001***	-0.001***	-0.001***	-0.001***	-0.012
	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)
Engine Power (MW)	0.271***	0.093	0.101*	0.102*	0.390
	(0.063)	(0.058)	(0.058)	(0.058)	(2.004)
Car age, years	0.009***	0.007***	0.007***	0.007***	-0.020
	(0.001)	(0.001)	(0.001)	(0.001)	(0.021)
Lagged relationship length with the incumbent	-0.053***	-0.062***	-0.059***	-0.060***	0.015***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
(Lagged relationship length with the incumbent)^2	0.014***	0.014***	0.014***	0.014***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IHS relative price change of incumbent at renewal, in %	0.013***		0.003***	0.003***	0.005***
	(0.001)		(0.001)	(0.001)	(0.001)
IHS incumbent's price difference from minimum price, in %		0.043***	0.042***	0.042***	0.058***
		(0.001)	(0.001)	(0.001)	(0.001)
The lagged reputation of the incumbent	-0.004**	0.016***	0.015***	0.015***	0.033***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Lagged Claims (=1 if a claim in the year before renewal)	0.009***	0.002	-0.002		-0.001
	(0.003)	(0.003)	(0.003)		(0.004)
The total sum of claims in The previous year, €				-0.000	
				(0.000)	
Observations	50,551	50,551	50,551	50,551	50,551
Number of consumers	20,759	20,759	20,759	20,759	20,759

Notes: Columns (1)-(4) of this table report marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations. Column (5) contains estimates of a linear probability model with consumer fixed effects. The mean probability of switching is 11%. Marginal effects (models 1-4) and parameter estimates (model 5) are reported with robust standard errors in parentheses.

*** $p<0.01$.
** $p<0.05$.
* $p<0.1$.

different types of claims and their interaction with pricing play in switching decisions. Table 2 summarizes the main findings in terms of marginal effects at mean values, with the exception of model 5.

The first observation is that in all the models 1-4, we see that age has a statistically significant impact on the probability of switching. An age difference of 10 years impacts the likelihood of switching by 1 percentage point relative to the base rate. Gender, however, does not play a role in model 1 or any of the subsequent models. We also include the length of the relationship in models 1-5, as this can be a proxy of the preference for a specific insurer. This is statistically significant in all of our models. The probability of switching decreases with each year that the customer stays with their current insurer. We add a quadratic term for relationship length into our models to explore this further and discover an interesting non-linearity. The coefficient for the quadratic length of the relationship becomes positive, meaning that after four years with the incumbent insurer, the probability of a switch becomes positive[3].

Model 1 uses the price change in the offer of the incumbent against the offer from the previous year only. The pricing action by the incumbent seems to play a role, as the coefficient estimate for it is statistically significant. The probability of the customer switching their current service provider increases by approximately 1 percentage point over the base rate for every price difference of 1% against the price of the previous year at mean levels.[4] The incumbent's average price fell by 2.6 percentage points against that of the previous year on average. Whether there was a claim before renewal seems to be relevant, but the reputation as a control variable for indirect learning is statistically not significant.

The other insurers are not aware of the claim submitted to the incumbent insurer and cannot base their pricing decisions on this, but the incumbent insurer is able to do that. That is why model 2 includes the difference between the incumbent insurer's price and the minimum price offered at renewal. There was an average price difference of about €32 or 8.12%. A difference of 1% in the price increases the likelihood of switching by about 4 percentage points over the base rate. A claim in the previous period does not seem to influence the decision to switch.

In model 3, we add both pricing differences into the model at the same time. The estimated coefficients for the marginal effects indicate that a rise in the price offer from the incumbent company would increase the probability of switching, but by far less than the difference against the minimum price offered does. A difference of 1% between the incumbent renewal offer and the minimum offer increases the switching

[3] An example from model 3 would be to use the estimated coefficients of -0.059 for relationship length and 0.014 for its quadratic term to estimate the chance of switching. The calculation of this would indicate that it takes on average -0.059/-0.014=4.21 years until the probability of the average customer switching becomes positive. Because of the inverse hyperbolic sine transformation we need to find $\frac{\partial\ (y)}{\partial\ (x)} = \frac{\beta}{\sqrt{x^2+1}}$. For example, if $\widehat{\beta}$=0.013 and the mean value of x is -1.08 (the mean value of the respective IHS variable is -0.934, hence the mean value of x would be (exp(x_{IHS})-exp(-x_{IHS})/2=-1.08) , we get $\frac{\partial\ (y)}{\partial\ (x)} = \frac{0.013}{\sqrt{-1.08^2+1}} = 0.01\langle /END\rangle$.We thank an anonymous reviewer for the suggestion that we point this finding out more clearly. It has indicated the arguments for *homo economicus* clearer and helped to improve the resulting conclusions.

[4] Because of the inverse hyperbolic sine transformation we need to find $\frac{\partial\ (y)}{\partial\ (x)} = \frac{\widehat{\beta}}{\sqrt{x^2+1}}$. For example, if $\widehat{\beta}$=0.013 and the mean value of x is -1.08 (the mean value of the respective IHS variable is -0.934, hence the mean value of x would be (exp(x_{IHS})-exp(-x_{IHS})/2=-1.08) , we get $\frac{\partial\ (y)}{\partial\ (x)} = \frac{0.013}{\sqrt{-1.08^2+1}} = 0.01\langle /END\rangle$.

Table 3
Impact of causes of claims on switching probability, marginal effects.

VARIABLES	(6) Consumer characteristics, price differences, and claims types	(7) Consumer characteristics, price differences, claims type and price change interacted
Gender (Male=1)	-0.000	-0.000
	(0.005)	(0.006)
Age, years	-0.001***	-0.001***
	(0.000)	(0.000)
Engine Power, MW	0.095	0.108
	(0.101)	(0.105)
Car age, years	0.011***	0.011***
	(0.001)	(0.001)
Lagged relationship length	-0.095***	-0.094***
	(0.009)	(0.009)
(Lagged relationship length)^2	0.017***	0.017***
	(0.002)	(0.002)
IHS price change of incumbent at renewal, in %	0.009*** (0.000)	0.005*** (0.001)
IHS incumbent's price difference from minimum price, in %	0.041*** (0.002)	0.041*** (0.002)
The lagged reputation of the incumbent	0.008** (0.004)	0.008** (0.004)
Lagged Third-Party Induced claim	0.079*** (0.006)	0.069*** (0.007)
Lagged Third-Party Induced Claim x Price difference in %		0.002*** (0.000)
Lagged Self-Induced claim	-0.023*** (0.007)	-0.031*** (0.007)
Lagged Self-Induced claim x Price Difference, in %		0.001*** (0.000)
Observations	9917	9917
Number of consumers	7841	7841

Notes: This table reports the marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations. The past experience of claims is split into different categories and interacted with price changes in model (7). The mean probability of switching is 11%. Marginal effects are reported with robust standard errors in parentheses.
*** p<0.01,]
** p<0.05 * p<0.1.

rate by almost 2 percentage points, whereas a change in the incumbent price only influences the switching probability by 0.2 percentage point over the base rate. This means that while a change in the incumbent's price slightly increases the probability of switching, what matters more is the price difference to other plans.[5,6]

Again, as in Model 2, a claim in the previous period is not statistically significant. This contradicts the learning hypothesis presented by Israel (2005) for the case of a claims experience and Miravete and Palacios-Huerta (2014) for spending on phone tariff plans.

Some earlier studies like Ho et al. (2017) have used the monetary value of a claim to study the switching decision, so model 4 uses the total sum of claims in euros instead of a claims dummy, but this also turns out to be statistically insignificant. This is why we build upon model 3 for the rest of the analysis.

We only present the marginal effects in Table 2, but the underlying coefficient estimates also have an intercept. Together with the error term, it describes factors that are not attributable to demographic factors or the utility from switching, or that are unobserved. The intercept is statistically significant and sizeable in all versions of our model. Some studies (Honka, 2014; Kiss, 2019) explain the intercept as the cost of search and switching.

In model 5, we validate model 3 by estimating a linear probability model with fixed effects for the combination of a car and its driver. The age of the driver and of the car increase linearly over time depending on the car owner, and their effect becomes statistically insignificant in model 5. Interestingly, the linear term for relationship length changes sign when individual fixed effects are considered, whereas the quadratic term remains similar to that in specifications 1-4. The individual fixed effects suggest the likelihood of switching starts to increase with each year of the relationship. The coefficients for monetary incentives to switch and learning effects are similar in their sign and order of magnitude to what they were in models 2-4.

The effect of age is statistically significant in all our models 1-4, indicating that older people are less likely to switch. This finding is in line with previous research (Boonen, 2016), though the magnitude of this coefficient is small.

We now develop two further models to disentangle the causes of the claims and their potential behavioral impact on switching. Claims are divided into three categories, as described in Section 3, with dummies for two of the categories. Table 3 presents the estimation results.

Model 6 unpicks the claims dummy used previously and splits it into the categories of Self-Induced and Third-Party Induced. The coefficients used in the previous specification remain of the same magnitude and significance, but a surprising effect appears, as a consumer who experienced a Third-Party Induced claim is more likely to switch at renewal. Quite the opposite story unfolds if there was a Self-Induced claim before renewal. If the consumer was at fault for a claim, their probability of switching falls relative to the probability with Other claim types, and the estimated coefficient is statistically significant.

The causes of the claims made with the incumbent insurer are known to the incumbent insurer but not to the other insurers, and so the price offer from the incumbent insurer at renewal might be affected by the claims submitted in previous periods. There is no market standard for no-claims-bonus calculations in Estonia, and in model 7, we consequently interact the difference in the incumbent price at renewal with different claims types. This helps us control for the learning effect separately from any price increases induced by the claims. The results of model 7 are similar to those of model 6, and the coefficient for the Self-Induced claim is even more pronounced than it is in model 6 after interaction terms have been used to control for price changes from previous claims. The interaction terms themselves have the expected signs.

The effect of Self-Induced claims on the probability of switching is negative, surprisingly, while the effect of Third-Party Induced claims is positive. This phenomenon is undoubtedly worth exploring further, especially as some studies indicate that psychological factors influence the switching responses of consumers to service quality. Consiglio and van Osselaer (2019) find for example that consumers with low self-esteem often do not switch when they experience poor service quality. Although the finding is contrary to the empirical findings in the literature on moral hazard, we can find support for this outcome in behavioral and psychology literature. Soscia (2007) for example studies consumer emotions and finds that gratitude is a significant driver of repurchase decisions.

A customer experiencing a Self-Induced claim might feel gratitude if they have a positive experience of the repair service. It could also be inferred from Soscia (2007) that a Third-Party Induced claim might cause feelings of anger, which would contribute to the switching behavior. The exact transmission mechanism of psychological factors in

[5] We thank an anonymous reviewer for the suggestion that we point this finding out more clearly. It has indicated the arguments for *homo economicus* clearer and helped to improve the resulting conclusions.

[6] An example from model 3 would be to use the estimated coefficients of -0.059 for relationship length and 0.014 for its quadratic term to estimate the chance of switching. The calculation of this would indicate that it takes on average -0.059/-0.014=4.21 years until the probability of the average customer switching becomes positive.

Table 4
Robustness checks for switching probability, marginal effects.

VARIABLES	(8) Car value[a]	(9) Active search[b]	(10) Price Difference from mean[c]	(11) Car make dummies	(12) Insurer dummies
Gender (Male=1)	-0.001	-0.001	-0.001	-0.003	-0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Age, in years	-0.001***	-0.001***	-0.001***	-0.001***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Engine Power in MW		0.105	0.107*	0.079	0.115
		(0.105)	(0.103)	(0.113)	(0.091)
Car value, in thousands of €	0.014**				
	(0.002)				
Car age, years	0.014***	0.011***	0.011***	0.009***	0.005***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged relationship length	-0.093***	-0.092***	-0.090***	-0.089***	-0.069***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
(Lagged relationship length)^2	0.017***	0.016***	0.016***	0.016***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
IHS price change of incumbent, in %	0.005***	0.005***	0.005***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IHS incumbent's price difference from minimum price, in %	0.041***	0.041***	0.045***	0.040***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
The lagged reputation of the incumbent	0.008**	0.008**	0.008**	0.006*	
	(0.004)	(0.004)	(0.004)	(0.004)	
Incumbent's price difference from the mean, in %			-0.001**		
			(0.000)		
Lagged Third-Party Induced claim	0.069***	0.068***	0.067***	0.067***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.000)
Lagged Third-Party Induced Claim x Price difference in %	0.002***	0.001***	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged Self-Induced claim	-0.031***	-0.032***	-0.032***	-0.028***	-0.026***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Lagged Self-Induced claim x Price Difference, in %	0.001***	0.001***	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
				(0.000)	
Active		0.080***			
		(0.019)			
Car make dummies				Yes***	
Insurer dummies					Yes***
Observations	9917	9917	9917	9917	9917
Number of consumers	7841	7841	7841	7841	7841

Notes: This table reports the marginal effects on the probability of switching away from the incumbent insurer found from random effects panel logit estimations that have changed the specifications of the previous models as robustness checks.
[a] model (8) uses Car Value instead of Engine Power as a proxy for consumer income.
[b] model (9) includes a small portion of Active customers who have opted to make the insurance decision by themselves. This was 1.45% of the total number of customers in our sample.
[c] model (10) uses the price difference between the incumbent offer and the mean price offered instead of the difference to minimum price offered.

combination with learning remains one avenue for future research.

6. Robustness checks

To test for the robustness of the results, we create other versions of our model 7, and the results are provided in Table 4. As Engine Power correlates positively with the value of the car, we use car value instead of engine power in model 7 to arrive at model 8, which is used for checking robustness. The statistical significance of the coefficients does not change from the earlier estimation results, and the car value itself is statistically significant.

We include a further dummy in model 9 describing whether the customer decided to take care of the insurance themselves. The proportion of consumers in our sample who did so was tiny at only 1.45%. This dummy is statistically significant. The probability of customers in the Active category switching is 8% higher than the probability for non-active consumers. No other coefficients change their statistical significance or their signs.

We also wanted to test whether the price difference from the mean value of all the offers made has an impact on switching. It turns out in model 10 that it is statistically significant, but the coefficient implies a minimal sensitivity to the difference in price over the mean value.

We add dummies for the make of car in model 11 for the makes that represent 5% or more of the total insured portfolio. These makes were statistically significant at the 99% level, with a few exceptions. However, adding dummies for the make of car into the model does not change the coefficient values or signs for the main explanatory variables. The main change is that the coefficient for the age of the car might correlate with the make of the car.

In model 12, we control for insurer dummies, since these might capture similar aspects to insurer reputation. We have left insurer reputation out of this specification. We can see that the impact of standalone dummies for claims is smaller than in model 7, indicating that insurer-specific effects are important.

The results in models 8-12 for the impact of demographic characteristics, price differences, other proxies for consumer preferences such as engine power or car age, and learning effects over time remain the same as in model 7.

The impact of demographic characteristics, price differences, other proxies for consumer preferences like engine power and car age, and learning effects remain the same across the different specifications in the robustness checks. These results are in line with the findings presented in Section 5.

7. Conclusions

This study provides empirical evidence for the probability of customers switching their car insurance provider in response to demographic and utility factors, and learning about the insurer's service quality. We ask how much such switching is driven by direct monetary effects, how much is attributable to characteristics of the car indicating brand preferences, and how much can be explained by the customer learning about the quality of the service.

In general, there is inertia, and the average probability of a customer switching service provider at renewal is 11%, while the average difference between the price of the option chosen and the cheapest offer was 8%. The triggers for switching reveal that a minor role is played by consumer characteristics like age, or like the age or value of the car as proxies for income. A consumer who is ten years older is one percentage point less likely to switch than the base rate.

As expected, direct monetary gains drive switching behavior, and the customer responses are as expected. A change in the price offered by the incumbent from that of the previous year is statistically significant. However, the difference between the price offered by the incumbent and the cheapest alternative has much more impact. A rise in price of 1% at renewal from the incumbent insurer makes switching 0.2 percentage points more likely on average than the base rate. Simultaneously, the difference between the incumbent offer and the cheapest option available increases the likelihood of switching by two percentage points over the base value. Even if the overall switching rate is not very high, the responses to changes within the choice set are more pronounced than those to changes in the default option. If consumers see their current price change, they might think about switching. They then compare that price with those of other plans and they only switch if they can actually save money by switching because there is a much cheaper option. Our study shows inertia to be smaller than earlier studies of adjustment costs have found, and *homo economicus* is more visible in our setting.

There was no direct cost involved from search and switching, so the main theoretical arguments for inertia would come from information processing, and learning as a particular case of it. Insurance is an intangible good, and consumers can only experience it directly when a claim happens. However, we did not find any universal relationship between a claim in the previous period and the probability of switching. After classifying claims into different categories, we find that consumers facing a renewal decision after a claim caused by a Third Party are more likely to switch than those who have experienced Other claims. If the claim were Self-Induced, the consumers are more likely to stick with their previous choice, even after interaction terms are used to control for the price impact of the claim. This outcome deserves further research into the psychological factors behind it and their impact on information processing.

Data availability

Stata dataset and do-file attached

Appendix 1. Glossary of the variables used

Variable	Definition
The probability of switching	= 1 if the service provider was changed in a given year and 0 otherwise
The probability of switching conditional on no claims	= 1 if the service provider was changed in a given year when no claims were handled and 0 otherwise
The probability of switching conditional on at least one claim	= 1 if the service provider was changed in a given year when at least one claim was handled and 0 otherwise
Consumer characteristics	
Gender	= 1 if policyholder is male and 0 otherwise
Age	years
Engine power	MW. Although commonly stated in kW, recalibrated into MW for better salience of the estimated effects
Car value	€ 1000
Car age	years
Active	The proportion of consumers who actively search for an insurer (= 1 if the consumer decided to deal with insurance themselves and 0 otherwise)
Product characteristics	
The relative price change of the incumbent insurer at renewal	in % against the price from last year
The relative difference between the incumbent and the minimum price offered	in %
The relative difference between the incumbent insurer offer and the mean price offered	in % against the mean price in the panel of offers
Service provider reputation relative to the sector's mean reputation in a given year	Reputation is measured as the difference between the number of consumer disputes relative to the market share of the insurer. To calculate relative reputation, the market average reputation is subtracted for a given year for a specific insurer.
The proportion of policies with at least one claim per year	= 1 if at least one claim was handled and 0 otherwise
Total claim amount per year	In € across all claims made under the policy in a given year
The probability of switching by claim type	
Self-Induced claim	= 1 if the claim was induced by the driver and 0 otherwise
Third-Party Induced claim	= 1 if the claim was induced by theft, vandalism, and collisions at third party fault and 0 otherwise
Other claims	= 1 if the claim was induced by fire, broken windscreens, wild animal collision, breakdown, or all other reasons and 0 otherwise

Appendix 2. Correlation coefficients for selected variables.

	Switch	Gender (Male = 1)	Age	Engine Power	Car age	Price change of incumbent	Incumbent price diff from min price	Lagged relative reputation	Lagged indication of at least one claim per year	Car value	Active search	Incumbent price diff from mean price
Switch	1											
Gender (Male = 1)	0.00	1										
Age	-0.04	0.03	1									

(*continued on next page*)

(*continued*)

Engine Power	0.03	0.16	-0.11	1								
Car age	0.08	0.01	-0.13	0.11	1							
Price change of the incumbent, in %	0.15	-0.00	0.04	0.01	-0.02	1						
Incumbent price diff from min price, in %	0.24	0.00	0.03	0.05	0.04	0.39	1					
Lagged relative reputation	0.01	0.02	-0.17	0.12	0.25	-0.01	-0.11	1				
Lagged indication of at least one claim per year	0.04	-0.00	-0.03	0.06	0.00	0.18	0.00	-0.02	1			
Car value	-0.02	0.09	0.04	0.40	-0.60	0.02	-0.17	-0.05	0.02	1		
Active search	0.09	-0.00	-0.01	0.03	0.04	0.01	0.01	0.02	-0.01	-0.01	1	
Incumbent price diff from mean price, in %	0.17	-0.02	0.07	-0.01	-0.01	0.39	-0.14	-0.09	0.13	0.06	-0.01	1

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Appendix 3

Publication III

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Explaining switching behavior: Consumer attention and choice in car insurance market

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A R T I C L E I N F O

Keywords:
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A B S T R A C T

This study investigates consumer search frictions and choices for Motor Own Damage insurance among vehicle lessees in Estonia. Using a consumer-level annual panel dataset from Estonia's largest insurance broker that comprises policy and insurance offers for 2010–2018, we apply a two-stage discrete choice model (building upon Hortaçsu et al., 2017) to identify sources of consumer inertia by separating attention and choice decisions given the documented switches to new providers. Consumers choose from a set of pre-listed offers corresponding to the best alternatives available in the market. Our results demonstrate that strong inertia is driven by consumer inattention, with considerable heterogeneity in inattention across consumer groups. Consumers' decisions to switch or stay with their current provider reveal substantial price elasticity and only a modest influence of brand preference. Our estimates are confirmed by multiple robustness checks.

1. Introduction

In 2025, Estonia became the final European Union (EU) country to introduce a motor vehicle tax, prompting public debate and petitions over its impact on household expenditures. This annual tax ranges from fifty to several hundred euros, with most car owners paying approximately €100.[1] While the tax is fixed by the government, the car insurance (also mandatory) market offers choices; however, many Estonian drivers seldom switch providers, missing potential savings of over €25 per year—approximately a quarter of the new car tax.

This evidence of substantial consumer inertia suggests bounded rational decision-making and the existence of behavioral biases (Hortaçsu et al., 2017; Abaluck and Adams-Prassl, 2021; Heiss et al., 2021). Recent literature has focused on measuring consumer inertia and inattention, proposing various methods and applying them across different contexts (see Ho et al., 2017; Hortaçsu et al., 2017; Heiss et al., 2021; Abaluck and Adams-Prassl, 2021). The interdependence of search and switching costs makes their separate identification challenging and warrants joint estimation (Wilson, 2012).

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[1] Based on Estonian Transport Authority https://www.transpordiamet.ee/en, the "average" car on the Estonian roads is a 10-year old Volkswagen Passat or Škoda Octavia. Based on their most common parameters, the annual car tax is around €100. In our sample the average annual tax rate may be different, since the leased cars are usually new or relatively new, and more expensive, but may also be less polluting on which the car tax depends on..

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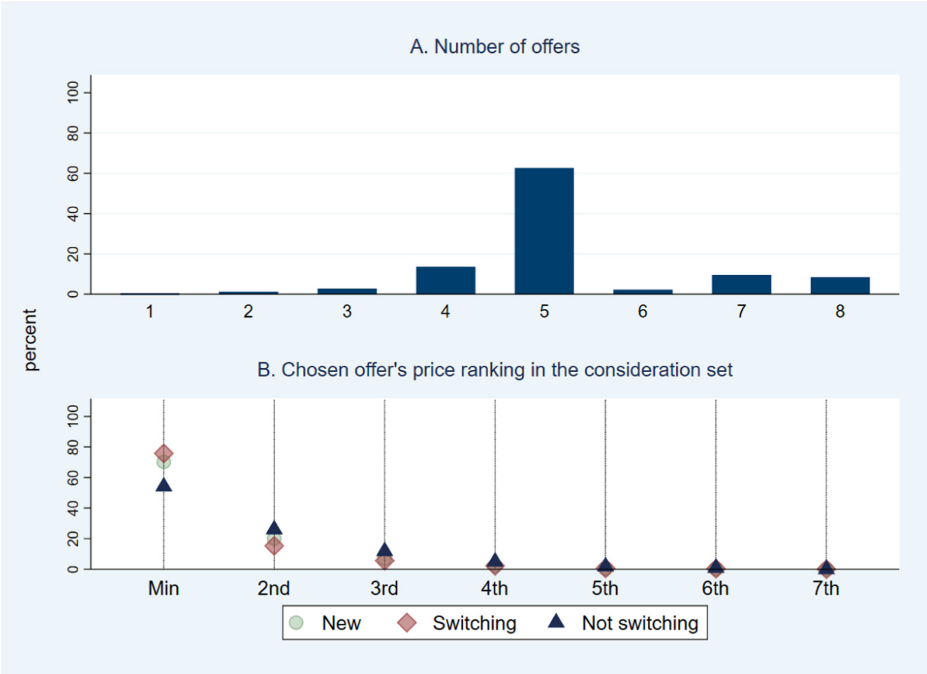

Fig. 1. Car insurance offers distribution: (A) the number of offers per customer and (B) the price rank of the chosen offer for new, switching, and non-switching customers.
Notes: Panel A depicts the number of car insurance offers presented to the customer. Panel B depicts the offer's price rank in ascending order, starting with the lowest (best) price offer, followed by the second-lowest, third-lowest, and so on. New customers are those whose policy started in the observed year and who do not have a record of past insurance providers. Switchers are recurring customers who have had different insurance providers in the past and current years. Non-switching customers are recurring customers who have had the same insurance provider in both the past and current year.

This study builds upon Hortaçsu et al.'s (2017) two-stage model, which identifies unobserved consumer attention and estimates separate parameters for the attention and choice stages of consumer decision-making. We use exclusive proprietary car insurance brokerage data from Estonia, a country where approximately 80 % of new private cars are purchased on a lease.[2] The dataset comprises Motor Own Damage insurance choices for car leasing customers. Car insurance is provided under two distinct cover: Motor Third Party Liability Cover, which is compulsory in every EU country, and Motor Own Damage Cover, which protects both the lessee and the leasing provider, and must be taken out under a standardized set of prescriptions by the leasing company. Since taking out insurance is compulsory upon leasing a car, there is no self-selection of customers into car insurance. The leading insurance broker gathers quotes from 11 insurance providers active in the market and presents the consumer with a list of about five standardized offers sorted by price (see also Fig. 1 in Section 3). All insurance providers operate in a competitive market regulated by the European Union Insurance Directive.[3]

In our setting, switching insurance providers involves no pecuniary costs for a car lessee, suggesting that switching costs are small and therefore that the observed consumer inertia in car insurance predominantly stems from search or attention frictions. In our dataset, 71.2 % of consumers did not switch in any observed year, 22.3 % switched provider once, and 6.4 % switched providers more than once. All quotes for making a decision to switch are already gathered at no extra monetary cost, but the information processing costs can still be substantial. Increasing effort associated with the search process may result in a conscious disregard of information (Cheremukhin et al., 2015). Furthermore, the choice of insurance brand has one peculiar feature—customers mainly learn about their provider following the filing of an insurance claim, hence there is a substantial delay in receiving information pertinent to re-evaluating their chosen brand's value.

Our study is distinctive for several reasons. First, our research setting is unique, allowing for more clean identification of attention and choice frictions. The quasi-experimental character of the observed data generation process isolates several potentially confounding

[2] This estimate is calculated by the authors based on statistics from the Estonian Transport Authority on newly registered cars (www.transpordiamet.ee) and the Estonian Leasing Association on the number of newly leased cars (www.liisingliit.ee)

[3] Directive (EU) 2016/97 of the European Parliament and the Council, https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX:32016L0097.

factors. In addition, the richness of the consumer variables enables us to control for past and present customer characteristics, thereby providing important insights into the factors that trigger consumer attention. The proprietary data, sourced from a major insurance broker containing standardized offers from 11 providers, eliminates heterogeneities in the customer-offer matching process. Our data covers most car insurance providers in the market. Since car insurance is an obligatory component of the leasing contract, there is no endogenous selection of customers Since the insurance broker standardizes the offer terms and procedures, there are no confounding factors arising from the customer's bargaining with the insurance providers. Additionally, because the offers are predefined by the broker, customers are not involved in the complicated sequential search process with its varying number of alternatives and search decision timings. Conversely, the consumers are exposed to a simple one-off choice between five pre-defined and standardized offers.

Our dataset includes customers' insurance choices and insurance claim filings. Customers' learning from filing claims influences their attention to renewal terms and eventual choice of insurance provider. Previous studies (Honka, 2014) have not explicitly controlled for the car insurance claims when predicting customer attention and explaining switching behavior. In addition to actual choice outcomes, we can observe the offer presented to switchers by their previous provider. Similarly, for non-switchers, we can see the lowest provided offer and its difference relative to the incumbent price offer. Deeming these outcomes proxies for the counterfactual, we find that it is difficult to rationalize substantial economic loss from consumer inertia without taking into account significant costs related to searching and processing information. Attention frictions in this context can also be magnified by the contemporaneity of the insurance and car leasing offers when pursued in a single customer–provider transaction (see Lipnowski et al., 2020).

To our knowledge, this is the first study to separately identify factors of inattention and choice in a two-stage empirical framework, using quasi-experimental data on insurance offers and consumer decisions, and a rich list of consumer characteristics and policy-related variables. Our novel findings are useful in multiple respects. The estimation approach, using a two-stage GMM model built upon Hortaçsu et al. (2017), fits our context well, featuring low switching costs and high unobserved search costs. Unlike in Hortaçsu et al.'s (2017) study, we can observe the number of switches for the same customer over 10 years, providing us with ample information for estimating consumer inertia in two stages, capturing both attention and learning effects, as well as choice factors. The contemporary and lagged variables, including the characteristics of the consumer, car, and past offers, as well as the time trend, inform the unobserved attention stage. The choice stage is identified using the price and provider brand information from alternative insurance offers. As a result, our model's predictions are highly plausible. The mean predicted probability of switching is 5.4 % and 7.7 % in the samples of single switchers alone and combined with multiple switchers, respectively. These predictions match well with the observed rates of switching (5.5 % and 7.8 %). The unobserved predicted mean for attention probability is 18.1 % in the sample of single switchers and 25.6 % in the broader sample, which includes multiple switchers. This indicates that multiple switchers are more likely to pay attention to the choice set. The mean switching-to-attention ratio of 30 % is similar for both subsamples, implying that the likelihood of switching conditioned on attention is uniform for both single and multiple switchers. Hence, the differences between single switchers and multiple switchers stem from the attention stage. Furthermore, the mean switching rate, conditional on attention, remains consistent across further subsamples used for baseline and robustness estimations.

We performed robustness checks, controlling for the validity of attention stage estimation using information from a subsample of customers who were all forced to pay attention since their contract terms changed, or the offer was not automated and required human interaction. Second, we estimated the model using a sample of young customers to control for the extent to which our results may be confounded by the unobserved state dependencies arising from unobserved past events and interactions with insurance providers for more senior customers. Finally, we controlled for the adequacy of choice-stage estimation using exogenous variation in choice factors, which arose from past legislative changes to the filing of car insurance claims. These insurance regulations changes altered consumers' incentives to consider offer features other than simply the price terms. None of these robustness checks refute our main findings; rather, they confirm the underlying implications of our empirical results.

This paper will proceed by reviewing insights from the literature on consumer choice frictions in Section 2. Section 3 describes our research context and presents the data. Section 4 explains the econometric model and identification strategy. Section 5 presents and discusses the empirical findings, and Section 6 concludes the paper.

2. Related literature

2.1. Theoretical foundations of consumer choice frictions

Expected utility theory posits that economic agents act rationally, which implies that consumers make utility-maximizing decisions (Von Neumann-Morgenstern, 1944). However, empirical observations reveal consumer inertia in repeated decision-making. Sims (2003) introduced rational inattention theory, which explains these observations. Rationally inattentive consumers maximize their imperfectly observed utility net of information acquisition and search costs (see also Stigler, 1961, and the literature review by Mackowiak et al., 2023). Consumer inertia in terms of brand choice, first investigated by Frank (1962) and Massy (1966), refers to the higher likelihood of a consumer choosing a product that they have purchased in the past (Dubé, Hitsch and Rossi, 2010). Beyond the cost of searching for the best provider, consumer choice frictions may arise for the costs of switching from one provider to another. Klemperer (1987) divides switching costs into transaction costs, learning costs, and contractual costs. For a more recent overview of a switching cost typology, see Burnham et al. (2003). Wilson (2012) argues for the joint consideration of search and switching costs. Buso and Hey (2021) experimentally tested Wilson's (2012) theory, proving the dominance of search costs in a sub-optimal choice strategy that triggers higher inertia.

The literature on consumer search frictions seeks to explain the extent to which the costly acquisition of information, information noise, or poor-quality information prevents consumers from gathering and exploiting full information on which to ground their decisions. Rational consumers evaluate the benefits of information search against the payoffs; whenever payoffs relative to the search effort are small, the consumers deliberately ignore relevant but costly information. Consumer decisions may also be interfered with by prior beliefs about the alternative options or state dependencies relating to earlier choices or events. Cheremukhin et al. (2015) assessed whether consumers' conscious disregard of information arises from rational ignorance or from physical limits, finding evidence to support the former argument. Their experimental results also show that consumers' rational inattention is endogenous since consumers weigh the costs of attention effort against the potential benefits of switching. The compatibility between consumer inattention and rational incentives has also been more recently discussed and investigated by Maćkowiak et al. (2023) and Dean and Neligh (2023).

Handel and Schwartzstein (2018) separate two strands of literature on choice frictions: search frictions and mental gaps. The latter line of research focuses on psychological distortions that interfere with the sorting and processing of information. Camerer (1999) summarized the early stages of the conjunction between economics and psychology literature, and a decade later, DellaVigna (2009) provided a comprehensive overview of deviations from rationality, including nonstandard preferences and beliefs. More recently, Gabaix (2019) surveyed varying manifestations of behavioral inattention and its psychological triggers.

Kordi Ghasrodashti (2018) and Liao et al. (2021), in the contexts of the home appliance market and smartphone brands, respectively, investigate the antecedents of brand-switching using the pull-push-mooring framework introduced by Bansal et al. (2005) in the brand management literature. The pull-push-mooring theory separates push factors—negative switch-triggering features of the existing brand—from pull factors—positive features of alternative brands that attract consumers away from their incumbent brand, and mooring factors—which lock customers to their incumbent brand. Kordi Ghasrodashti (2018) found that price is the only dominant push factor inducing brand switching in the context of home appliances, while Liao et al. (2021) demonstrate the importance of regret as a push factor that prompts consumers to switch away from their incumbent smartphone brand in China. Switching costs constitute an important mooring factor, and the attractiveness of alternative brands serves as the main pull factor.

The literature on brand management (e.g., Kordi Ghasrodashti, 2018) and the psychology-related strand of individual decision-making (Camerer, 1999; DellaVigna, 2009; Gabaix, 2019) complements the line of rational inattention research that extends to examining the deeper mechanisms underlying individual decision-making.

The market implications of consumer inertia have raised concerns about an increase in firms' monopoly power. Polyakova (2016) identified substantial welfare losses from switching frictions in the US health insurance market. Conversely, Wisnicki (2022) demonstrated that consumer inertia may also improve consumer welfare and market equilibrium by creating incentives to increase product or service quality.

2.2. Empirical evidence on consumer inertia

The empirical literature provides evidence of substantial consumer inertia, primarily arising from search frictions, with laboratory experiments revealing inconsistencies in individuals' choices and preferences (Thaler and Shefrin, 1981; Charness and Rabin, 2002; Cheremukhin et al., 2015). Empirical studies have sought to understand the extent to which choice decisions are governed by rationality arguments or by alternative explanations such as mental gaps (Handel and Schwartzstein, 2018) or physical limitations (Cheremukhin et al., 2015). The literature on the measurement strand has shown that the results of laboratory experiments may differ from those of field studies and that individuals in real-life situations may adjust their decision-making using information updating (Levitt and List, 2007) or enter into bargaining with the counterparty (DellaVigna and Malmendier, 2004).

Empirical research investigating inertia faces challenges in identifying underlying mechanisms. Attention and choice decisions are endogenous and warrant joint estimation (Wilson, 2012). Search and switching costs are only separable according to observation in limited contexts (e.g., Gargano and Rossi, 2018).

The two-stage model developed by Hortascu et al. (2017) using data from the electricity market in Texas, US, recognizes and addresses the complexities of endogenous choice, incorporating aspects of consumer heterogeneity and state dependence. Two-stage models establish separate equations for the search and choice decisions, facilitating the identification and deeper understanding of the mechanisms underlying consumer choice. A single-stage discrete choice model is usually unable to separate search from switching costs unless both are fully observed. Two-stage consumer choice modeling is therefore becoming a contemporary standard in empirical research (see also Ho et al. (2017).

There are two domains of field studies that are closely related to our research case. The first involves health insurance (see Handel, 2013; Handel and Kolstad, 2015; Ho et al., 2017; Heiss et al., 2021; and Abaluck and Adamas-Prassl, 2021). The other deals with other non-tangible goods and services with an intertemporal consumption character, such as services in the electricity market (Hortascu et al., 2017), telecom subscription goods (Miravete and Palacios-Huerta, 2014), investment accounts (Hortaçsu and Syverson, 2004; Hastings et al., 2017), and non-life insurance goods (Schlesinger and Schulenburg, 1991; Honka, 2014).

Berger et al.'s (1989) study was one of the first attempts to empirically measure switching costs in the car insurance market. In their research, switching costs relate to a certain threshold that triggers consumers to switch away from the incumbent provider, given the price difference between the current insurer and the competitors' offers. Schlesinger and Schulenburg (1991) considered both switching and search costs in the German insurance market, examining product heterogeneity and the pricing actions taken by the insurer. In a subsequent study, also based on German survey data and using a simple probit model, Schlesinger and Schulenburg (1993) estimated insurance customers' search and switching costs as determinants of their switching decisions. They constructed an "information index" that measures search costs and provides information about consumers' subjective price rankings relative to the actual prices of insurance offers.

Handel (2013) established that consumer inertia in health insurance markets amounts to approximately $2000 in annual losses for policyholders due to suboptimal insurance plans. This outcome can be considered rational inattention in the context of high search and information processing costs or if the consumers have biased beliefs. Handel and Kolstad (2015) argue that consumers tend to overpay for wider insurance coverage, irrespective of eventual deductibles and out-of-pocket expenses, with an estimated overspend of around $2300 per year. Abaluck and Gruber (2016), Ho et al. (2017), and Abaluck and Adams-Prassl (2021) found that health insurance beneficiaries in the United States leave approximately $300 on the table annually due to inertia in their Medicare Part D drug coverage choices.

Regarding investment choices, Hortaçsu and Syverson (2004), studying S&P500 funds and indexes, and Hastings et al. (2017), investigating Mexico's privatized mutual funds, revealed that customers choose a remarkably high proportion of higher-fee funds among essentially homogeneous investment options.

Inattention-related choice frictions are heterogeneous (Cheremukhin et al., 2015; Heiss et al., 2021). Heiss et al. (2021) demonstrate high individual variability in attention, depending on personal characteristics and preferences, finding that females and individuals under the age of 70 are more likely to pay attention to US Medicare Plan D health insurance choices. Hortaçsu et al. (2017) and Miravete and Palacios-Huerta (2014) demonstrated that consumer attention and decision-making are influenced by past events. Heiss et al. (2021) conclude that attention is pronounced given the difference in pricing over the previous year, i.e., existing pricing, and if the consumer's existing choice is impaired relative to alternative choices. Our study considers both customer heterogeneity and state dependence aspects.

The empirical literature has also investigated consumer choice and inertia in the car insurance context. Honka (2014), using evidence from the US car insurance market, decomposed inertia into search and switching costs, exploiting information on customer satisfaction. She attributed the uncorrelated variation of switching with customer satisfaction to switching costs and the correlated variation to search costs. She discovered that search costs are the primary source of high customer retention and that customer welfare could be improved by 17 times if the search costs were removed. She reported that search costs exhibit considerable heterogeneity, averaging from $35 to $170. The more homogeneous switching cost is around $40. According to Honka's (2014) study, the average price elasticity across all companies in her sample is -1.08. She also presents some counterfactuals. If search costs were eliminated, 60.4 % of consumers would switch, and if switching costs were eliminated, 30.6 % of consumers would switch. Eliminating both costs would result in a switching rate of 61.9 %.

Kiss (2019), investigating the switching of motor third-party liability insurance providers in Hungary, used a two-stage model and a natural experiment—a government-run campaign—that provided exogenous variation for identification. Jõeveer and Kepp (2023) studied the consumer learning effects of observed switches in the Estonian car insurance market. Using a simple logit model, they investigated the switching and learning effects of customers' repeated choices. Learning effects in repeated choices have also been reported by Miravete and Palacios-Huerta (2014) and Cheremukhin et al. (2015). Jõeveer and Kepp (2023) did not differentiate between search and switching costs; however, they found associations suggesting that both the rational choices regarding price differences and psychological factors associated with different types of insurance claims (whether caused by a third party or self-induced claims), can trigger a switch. We use similar sources of information, but the current study employs a broader sample of consumers and a more recent dataset. We use the same wealth of information on consumer variables but employ a more sophisticated framework that identifies unobserved inattention and separates it from the consumer choice decision.

A common limitation in the empirical literature (Hauser and Wernerfelt, 1990; Shocker et al., 1991) is that the consumer consideration set is not fully observed, and several general assumptions must be made and probabilities assigned to possible options that the consumer might consider. Conversely, our data and the underlying data generation process enable us to observe the full consideration set for each consumer. All observed customers face a standard offers template, most of which includes five customized offers. In contrast, the pricing and other terms of that choice set can be no worse than any other available market option. Therefore, the customers have no incentive to search for alternative offers elsewhere. The standardized offers procedure removes noise on the supply side, ensuring that our estimation results on consumer choice are not confounded by offer supply-side variation and accurately reflect consumers' decisions.

3. Data and descriptive evidence

We sourced data from the largest insurance broker operating in Estonia. During the 2010–2018 observation period, approximately 80 % of all new cars sold were leased,[4] and the broker served and administered insurance policies for major car leasing companies that accounted for approximately 50 % of the total market.[5] Our study focused on individual consumers' choices, so we excluded all commercial car lease customers from the dataset. The broker combined and anonymized insurance offers, claims, and policy data. The standardized offers from 11 different insurance companies can be observed, presented to consumers at no extra cost. In Estonia, the insurance distribution that we observe for leased cars, is designed in collaboration of the leasing companies, the broker, and the insurers. The system aims to guarantee that all leased cars are covered at the inception of the lease contract and that insurance contracts are closed at market terms. Broker sets up an insurance distribution system that standardizes the insurance terms, including the list of perils and deductible levels, and provides a comparable insurance offers set for the car leasing customers. "

[4] This estimate is calculated by the authors based on statistics from the Estonian Transport Administration on newly registered cars (www.transpordiamet.ee) and the Estonian Leasing Association on the number of newly leased cars (www.liisingliit.ee).

[5] This estimate is computed by the authors based on the statistics of the Estonian Leasing Association about the number of new leased cars (www.liisingliit.ee) and proprietary data of the broker concerning numbers of distinctive lease-bound quotes issued.

Each customer, meaning a vehicle lessee, receives approximately five standardized offers sorted by price, as depicted in Fig. 1. Independently of one another, insurance providers generate their offers in real-time based on the characteristics of the customer and the leased car. Because the leasing companies require that insurers do not discount their leasing-bound quotes in other sales channels, the pricing for the choice set is representative of all offers presented to the consumer by the same insurers. An illustrative example of the standardized offer is presented in Appendix B.

Fig. 1(A) shows that most customers, almost 63 %—received five offers and that deviations from this choice set are uncommon. More than three-quarters of the switching customers and over 70 % of new customers chose the lowest-priced offer, while only 54 % of the non-switchers received a renewal at the minimum price given their offers set (see panel B of Fig. 1).

The offers account for the deductible levels and the characteristics of the insured persons and cars. The prescribed cover can only be provided at two different levels of deductibles that will be presented to the customer as two alternative choices, containing at least five independent offers for each deductible level. The deductibles in our sample range from €100–200, and high deductibles have values of €300 or higher. <4 % of customers have chosen the higher deductible. Customers can switch from a higher deductible to a lower one and vice versa. During the period observed, the grouping of deductibles into “lower” and “higher” categories, as well as the way these options are presented to the customer, have remained the same.

Our data also includes insurance claims for all policies issued between 2010 and 2018, matched to their respective policies, with both claim and policy datasets coming from the same broker. Having made a claim and experienced the repair service might affect a customer’s decision to pay attention to the renewal choice.

In addition to the customer-level policy data, we gathered data for insurance providers, including the year of establishment of the insurance brand in Estonia and their market shares.[6] Beyond the offer price, consumer preference for a particular insurance brand could potentially be an important factor of consumer choice.

It is important to note that the choice of insurance offer is made jointly and simultaneously with the car leasing offer, and this could have implications for consumer attention and choice (for research on bundled offers, see Rao et al. 2018; Li and Song, 2022). Given our context, consumers are mostly attuned to the car purchase and lease offer. However, the insurance offer, presented to the customer immediately after the car lease offer, is completely independent of the car leasing contract terms, and there is no bundling in pricing or in any other terms. However, the contemporaneity of the two offers may affect consumer attention and choice.

The combined offer, policy, and claims datasets form an unbalanced panel for estimation, with three features that make the data formation unique. The first is that the car leasing customer does not need to compile the offers’ set themselves. Instead, the insurance broker creates the list of standardized offers and presents it to all leasing customers alongside their car purchase and lease offer. Therefore, the choice set is generated exogenously by a third party, and this eliminates much of the heterogeneity and complexity in customer search strategies (such as bargaining or sequential search). Second, since all leasing customers are required by their car leasing company to take out insurance, there is no self-selection of customers into insurance, eliminating the potential issues of endogenous sample selection. Finally, the set of offers is standardized to comply with the requirements of all leasing companies, and the competing insurance offers are presented to the consumers to facilitate comparison. Standardization includes the minimum leasing cover, the list of perils, and deductible options. The only truly varying choice factor is the insurance offer price. Given that price is the main choice argument, there is also very low incentive for the insurer to deviate from the minimum standard conditions by providing higher cover or other more favorable conditions for the customer, as these would result in a higher price of the offer. Table 1 presents the variables and their descriptions and sources. Table A1 in the Appendix provides summary statistics.

The process of generating policy data is as follows. When the customer signs a new lease contract, the leasing company requires that the leased vehicle be insured against a prescribed list of perils that is known as comprehensive cover (minus the Third-Party Liability cover, which is required, but insured under a separate policy). The broker submits an electronic quote request, containing pricing parameters or characteristics of the customer and the leased car, to a panel of insurers. The insurers respond with their prices, which are calculated in real time and independently of other providers, and the broker combines their responses into a panel offer. The insurers on the panel accounted for >80 % of the total car insurance volume in the market during our sample period.

Fig. 2 shows that, on average, prices tend to drop with customer tenure, including non-switchers. There are two reasons for this. First, the value of the car depreciates over time, reducing the value of the insurance coverage. Second, and more importantly, the incumbent insurer knows that it needs to compete at all renewals.[7] The set of offers (see Appendix B) is standardized so that no insurer has any advantage over the others in targeting the consumers, nor can they interact with the consumer during the quoting process. The only winning strategy for the provider is to quote a competitive price for both higher and lower deductible levels and indirectly influence consumer attitude by increasing its presence and brand name recognition in the market (note that the offers set presented to the consumer only displays the names of the brands but does not include any other brand or marketing-related information, such as logos, etc.).

All policies have a one-year term, and 30 days before expiry, the broker sends the customer a renewal offer featuring the same standardized set of perils for both deductible levels from different insurers. The customer can easily change their insurer by simply replying by e-mail or making a phone call to communicate their choice of insurer for the next year. If the customer does not respond to the renewal offer, and the price difference from the same insurer is <10 % against the prior year, their insurance will continue with the

[6] The two oldest insurance brands were both established in 1993 and the two most recent brands were established in 2013 and 2015, respectively.

[7] Pricing strategy may manifest differently for the direct customers of insurers when a broker is not involved. It is not uncommon to intentionally market lower prices to new customers that will be compensated for with renewals when the likelihood of a customer receiving competing offers is low and their inertia can be maximized for profit.

Table 1
Description of variables and data sources.

Variable name	Variable description
Dependent variable	
Switching	An indicator of whether a consumer switched away from the previous insurance provider in a given year or not. 1 switch, 0 otherwise
1st stage: Attention, decision to make a choice	
Lag Ln price of the chosen offer in previous year	Log price (in euros) of the insurance premium offer that was chosen over last period.
Lag offer's price rank	The price rank of the last offer, where the minimum (best) price offer assumes rank 1, the second lowest price rank 2 etc.
Customer tenure	Number of years with the same insurance provider
Lag Deductible	Last years' choice of deductible: 0 – high deductible, 1 – low deductible
Lag count of claims (self)	Number of self-induced claims in past years
Lag count of claims (third)	Number of third-party induced claims in past years
Lag count of claims (other)	Number of other claims in past years
Log car value	Log of car value in thousands of euros
Log engine power	Log value of car engine power in kW
City	Urban/rural area of car registration: 1 city, 0 otherwise
Female	Indicator of gender: 1 female; 0 male
Age	Age of the customer, in years
Ln year trend	Log (current observation year – first year of observation)
2nd stage: Choice of insurance offer	
Ln price of the chosen offer	Log price (in euros) of the insurance premium offer that was chosen.
Brand*	Years since the insurance provider of the chosen offer was first established in Estonia.
Moments' weighting	
Ln size	Log size of the insurance provider in number of customers

* Data source: Insurance policy data by insurance broker, proprietary data. Insurance brand establishment years in Estonia were retrieved by the authors from the insurers' websites.

same insurer. If the price difference is greater, the broker will attempt to re-negotiate the renewal pricing with the current insurer and contact the customer with the revised offer. If the customer still does not respond, the policy will continue with the same insurer.

It is thus clear that customer attention to a renewal offer can manifest in distinct ways. If the renewal offer attracts the customers' attention because it is satisfactory, they will continue with the same insurer. The attention paid to that decision is unobserved. Alternatively, they might want to change insurer, in which case the attention paid can be observed by the researchers from the information recorded in the Switch variable (described later). The third possibility is that the customer paid no attention to the renewal offer and stayed with the same insurer. We will revisit this point when describing the methodology in Section 4.

We track the past and current offers for all customers and whether they continued with their incumbent provider or whether they switched to a new insurance provider, and at what price. We can also observe the lowest price offer presented and whether the customer chose that offer or opted for (stayed with) a higher price offer from another (incumbent) provider. Fig. 2 depicts the distributions of relative price gains and losses for switching and non-switching customers. The upper panel (panel A) shows that the relative (percentage) price differences of past provider's offers are tilted towards lower (more favorable) prices for the non-switchers, while the opposite is true for the switching customers. Therefore, a higher share of switching customers received price offers from their past provider that exceeded the price they paid the previous year. The differences on the gains side (left part of the distribution) are less notable, indicating that customer switching is more frequently triggered by price increases than by price declines. On average, those who stayed with their incumbent provider renewed at a price that was 6 % lower than the previous year's offer, while those who switched would have had to pay almost 2 % more than their past offer, if they stayed with their incumbent provider.

Panel B in the center of Fig. 2 illustrates the gains for the switchers when comparing their chosen offer price in the current year with their previous provider offer from the past year (left) and from the current year (right). Both distributions demonstrate considerable probability mass on the negative side of the distribution (consumer gains), clearly contrasting with the upper panel (Panel A), which shows price changes stemming from past providers' offers. Consumers who switched gained 13 % lower premiums relative to the price they paid to their past provider a year ago, and they paid nearly 15 % less compared to the price offered by their past provider in the current year. The average savings for switchers was €72 compared to the price offered by their incumbent provider. The bottom panel (panel C) depicts the relative price difference with respect to the lowest (best) price offer in the current year. A high probability mass near zero shows that the bulk of customers have chosen the lowest or near-lowest price offer. Nevertheless, it is evident that the

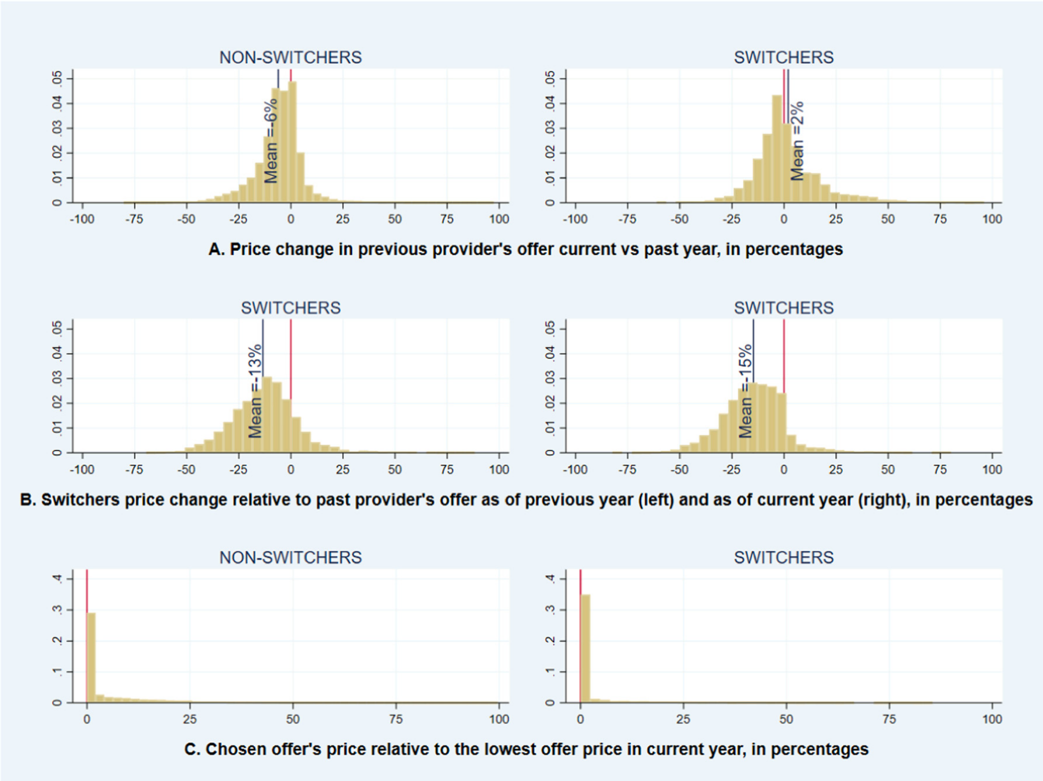

Fig. 2. Relative price change distributions of car insurance offers for switchers and non-switchers.
Notes: Panel A shows price change distributions in percentages, comparing the past provider's (provider in year T-1) price offers between the current and past year ({current price – past price} / past price *100) for the non-switching customers (left) and switching customers (right). Panel B presents the offer price gain/loss distributions for the switchers' current year vs past year (left) and current year's chosen offer vs current year's past provider's offer (right). Panel C plots the relative price differences with respect to the lowest (best) price offer in the current year for the non-switchers (left) and for the switchers (right).

positive tail—the higher price gap relative to the best price offer—is more pronounced for non-switchers. On average, non-switchers left €25 on the table, paying their incumbent provider a price nearly 7 % higher than the lowest available offer.

4. Econometric model

The estimation strategy implements and augments Hortaçsu et al.'s (2017) model, which simultaneously estimates individuals' decisions in two stages—deciding to pay attention to car insurance offers and choosing an insurance provider from a pre-set list of offers. The decision to pay attention and make a choice has two potential outcomes—retention or switching to a new provider. Consumer inattention invariably results in retention. Retention, however, may also result from a consumer's informed decision to stay with their current provider. Hence, the consumer retention outcome does not indicate whether the customer paid attention or not. The switching outcome, in contrast, always indicates that a customer has paid attention to alternative offers (see Fig. 3).

The binary dependent variable is the observed year-on-year switch from the current insurance provider to the new provider, conditional on the consumer having decided to pay attention and choosing accordingly. The empirical approach identifies separate parameters for both decision stages and allows for heterogeneity across individuals and over time by using panel data. The likelihood of paying attention to car insurance offers depends on individual characteristics, car attributes, and the consumer's experience with the current insurance provider.

During the first stage, the attention probability of an individual who is a customer of the provider (denoted by k) is defined in the standard binary logit form. The new insurance provider is denoted by j, implying that in the case of retention, $k = j$. Time dimension t marks annual observations, and z_{it} is the vector of varying customer–year individual characteristics, car attributes, insurance claims, premium prices, and other features of the existing insurance policy. The logit specification constitutes the first step or the consumer attention decision step for joint modelling of consumer switching decision parameters.

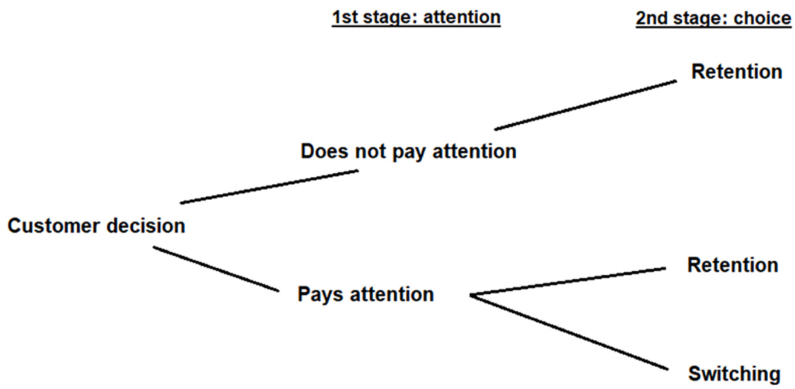

Fig. 3. Customer's two-stage decision-making process.

$$\lambda_{it}^{k} = \frac{\exp\left(z_{it}^{'}\gamma\right)}{1 + \exp\left(z_{it}^{'}\gamma\right)} \tag{1}$$

In the second stage—choosing an insurance provider—the consumer seeks an outcome from a set of offers that maximizes their utility.

$$U_{ijt} = x'_{jt}\theta + \varepsilon_{ijt}, \tag{2}$$

where x_{jt} is the vector of insurance provider characteristics, including the log premium price offers by the competing insurance providers and the insurance provider brand variable, measured as years since the brand was first established in the Estonian market. Both variables in the choice equation are independently generated by the other insurance providers and therefore satisfy the assumptions for conditional logit specification. The specification of our choice equation resembles the one used by Hortaçsu et al. (2017). For the attention equation, we broadly follow Honka (2014), with the exception of constraints due to certain data limitations.[8]

The conditional logit model (see McFadden, 1974) estimates the probability that individual i opts for the offer from insurance provider j in year t.

$$P_{ijt}^{Choice} = \frac{\exp\left(x_{jt}^{'}\theta\right)}{\sum_{k\geq 1} 1 + \exp\left(x_{jt}^{'}\theta\right)}. \tag{3}$$

The first and second stages are simultaneously estimated using a Generalized Method of Moments (GMM), where the moment conditions arise from the observed customer switch. The joint estimation agrees with Wilson (2012), who claims that search and switching decisions must be considered together.

The GMM objective function for estimating the parameters of the attention and choice stages (γ,θ) of switching is $\min \eta(\gamma,\theta)' W \eta(\gamma, \theta)$. The sample moment η_{jt}^{k} is expressed as follows:

$$\eta_{jt}^{k} = \frac{N_{jt}^{(k)} - \left(\sum_{i\in B_t^{(k)}} \lambda_{it}^{(k)} P_{jt}\right)}{N_t^{(k)}}, \tag{4}$$

where $N_{jt}^{(k)}$represents the observed count of consumers who switch from provider k to provider j in year t, and the expression $\sum_{i\in B_t^{(k)}} \lambda_{it}^{(k)} P_{jt}$ represents the expected number of switchers. Subscript $i \in B_t^{(k)}$denotes the consumers belonging to a set of policyholders with insurer k at year $t-1$. The decision and choice probabilities $\lambda_{it}^{(k)}$ and P_{jt} are as defined above in Eqs. (1) and (3). The denominator $N_t^{(k)}$ adjusts the moments by variance that arises from the number of customers who hold their policy with a specific insurer (the larger the customer base, the larger the variance).

The identification relies on the assumption that the decision to pay attention is a function of the previous insurance provider k and not of the next provider j. This condition corresponds with the "push" rather than "pull" triggers of a consumer's decision to stay with the current provider or look for a new one (Hortaçsu et al., 2017). On the contrary, the probability of choice from a set of offers is a function of the next provider j and not the previous provider k. In addition, the identification requires that the customers consider all

[8] Honka (2014) has a somewhat wider list of socio-demographic variables and also has customers' credit history and consumer survey information but no claims data.

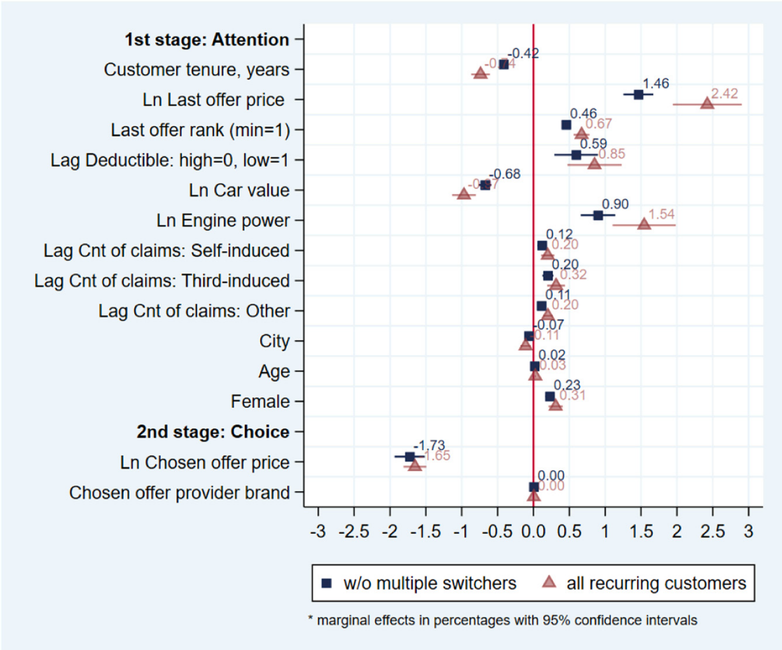

Fig. 4. Estimated marginal effects in percentages of switch rate for the sample excluding and including customers who switched insurer more than once.

Notes: Marginal effects in percentage terms at variable mean values with 95 % confidence intervals. Sample of recurring customers with and without multiple switchers. The dependent variable is an indicator of whether a consumer switched away (switch=1) from the previous insurance provider or not (switch=0).

Attention equation (1st stage): Customer tenure refers to the number of years spent with the same insurance provider. The last offer price is the log price of the offer chosen in the previous year. The last offer rank is the price rank of the last offer, where the minimum (best) price offer has rank 1, the second-lowest price has rank 2, etc. A deductible is a dummy variable assuming a value of 1 if a customer takes an offer with low deductibles, and is 0 otherwise. The count of claims refers to insurance claims over the past years and is divided into three categories: self-induced, third-party induced, and other claims. Car value is measured in thousands of euros. Engine power is expressed as a log value in kilowatts. City and Female indicate urban or city area of car registration and the car lessee being female. Age refers to the customer's age in years. The attention equation includes a logarithm annual trend and a constant term that is not depicted on the graph but is reported in Table 3 in the current section.

Choice equation (2nd stage): The chosen offer price is the log price of the chosen offer in the consideration set. The chosen offer provider brand refers to the number of years the brand has been established in the Estonian car insurance market.

offers "on equal terms" and that they do not have any private information on alternative providers based on their prior experience. This assumption is met upon not knowing other providers except for the previous insurance provider.

The vast majority of our observations (93.5 %) come from customers who stayed or made a single switch; only 5 % of observations relate to customers who have made two switches, and 1.5 % to customers with more than two switches. The estimations are provided for the sample with and without multiple switchers (see Fig. 4 and Table 2 in Section 4). The standard errors for the GMM coefficient estimates are clustered by customers. The marginal effects were calculated at variable mean values. The technical details are provided in Appendix C.

We conducted three separate robustness checks addressing (1) model sensitivity to potential confounding from customers past experiences with insurance providers; (2) model sensitivity to unobservables in the attention equation; and (3) model sensitivity to

Table 2
Marginal effects at the mean for the sample with and without multiple switchers.

Probability of switching the insurance provider	multiple switchers excluded		Total sample
	Age below 34	All age groups	
1st stage: Decision to pay attention			
Customer tenure, years	−0.00592***	−0.00416***	−0.00738***
	(0.00146)	(0.00029)	(0.00066)
Lag ln price of last offer	0.00746***	0.01463***	0.02423***
	(0.00159)	(0.00107)	(0.00245)
Price rank of last offer	0.00364***	0.00455***	0.00670***
	(0.00074)	(0.00025)	(0.00057)
Lag deductible, low	0.00223*	0.00595***	0.00851***
	(0.00125)	(0.00155)	(0.00194)
Ln car value	−0.00353***	−0.00676***	−0.00969***
	(0.00063)	(0.00046)	(0.00085)
Ln engine power	0.00184*	0.00900***	0.01543***
	(0.00103)	(0.00123)	(0.00225)
Lag count claims: Self	0.00039	0.00119***	0.00198***
	(0.00041)	(0.00033)	(0.00048)
Lag count claims: Third	0.00099*	0.00200***	0.00315***
	(0.00055)	(0.00039)	(0.00064)
Lag count claims: Other	0.00099**	0.00111***	0.00201***
	(0.00036)	(0.00021)	(0.00033)
City/Urban	−0.00035	−0.00066**	−0.00110**
	(0.00029)	(0.00027)	(0.00037)
Age	0.00047***	0.00016***	0.00026***
	(0.00012)	(0.00002)	(0.00003)
Female	0.00083**	0.00227***	0.00309***
	(0.00036)	(0.00033)	(0.00051)
Log year trend	0.00191***	0.00361***	0.00473***
	(0.00046)	(0.00038)	(0.00058)
2nd stage: Choice decision			
Ln price of chosen offer	−0.00518***	−0.01726***	−0.01652***
	(0.00058)	(0.00107)	(0.00081)
Brand of chosen provider	0.00002*	0.00004**	0.00005***
	(0.00001)	(0.00001)	(0.00001)
Observations	9668	47,433	52,344
Customers	4381	17,408	18,613
GMM-criterion	0.00327	0.00266	0.00344
Mean predicted attention	0.20876***	0.18064***	0.25623***
	(0.00325)	(0.00114)	(0.00144)
Mean predicted switch	0.06651***	0.05505***	0.07798***
	(0.00253)	(0.00105)	(0.00117)
Mean of actual switchers	0.06514***	0.05430***	0.07692***
	(0.00120)	(0.00042)	(0.00054)

unobservables in the choice model.

First, we estimated the model using a sample of customers under the age of 34, excluding multiple switchers. This sample helps control the effects of left censoring for older customers whose unobserved past events might confound our identification. The results from this sample of younger customers retain all signs of the estimated parameters. The attention and switch predictions match the ranges estimated for the broader samples with and without multiple switchers (see Table 2 in Section 4).

Next, we separated a sample of customers who had to pay attention to insurance offers, Pr(Attention)=1) because of changes in their insurance contracts (e.g., deductibles) or for other reasons triggering human interference in otherwise automatically generated offers. This sample comprised 3951 individuals, forming a sample of 5680 observations between 2010 and 2018.

The estimates for the choice equation are presented in Table 3 and Fig. 5 in Section 4, and are compared to the results from the broader sample with the predicted attention rate. The regression outcomes reveal that all signs for the coefficient estimates remain consistent. In contrast, the offered price variable and the brand variable coefficient estimates exhibit larger magnitudes than the estimates from the broader samples with predicted attention probabilities. This suggests that the two-step estimation framework, in general, is robust and provides coefficient estimates that are at the lower bound of the true parameter estimates.

Table 3
Marginal effects at mean for the choice equation in the samples with incomplete and full attention, i.e., Pr(Attention)=1.

Probability of switching the insurance provider	Pr(Attention)=1		All Customers	
Weighted		Unweighted	w/o multiple switchers	Total sample
2nd stage: Choice decision				
Ln Price of chosen offer	−0.03009***	−0.03192***	−0.01726***	−0.01652***
	(0.00327)	(0.00387)	(0.00107)	(0.00081)
Brand of chosen provider	0.00100***	0.00162***	0.00004**	0.00005***
	(0.00012)	(0.00014)	(0.00001)	(0.00001)
Observations	5680	5680	47,433	52,344
Customers	3951	3951	17,408	18,613
GMM-criterion	0.00916	0.01629	0.00266	0.00344
Mean predicted switch	0.24176***	0.20844***	0.05505***	0.07798***
	(0.00167)	(0.00121)	(0.00105)	(0.00117)
Mean of actual switchers	0.21473***	0.22465***	0.05430***	0.07692***
	(0.01231)	(0.00554)	(0.00042)	(0.00054)

Notes: Marginal effects in percentage terms at variable mean values. Full attention, Pr(Attention)=1, applies to customers whose insurance offer was not automatic because they changed their car or had other reasons that the offer necessitated human interaction, and thus, paying attention to the offer. Weighted estimates are adjusted by sampling weights (inverse probability weights).

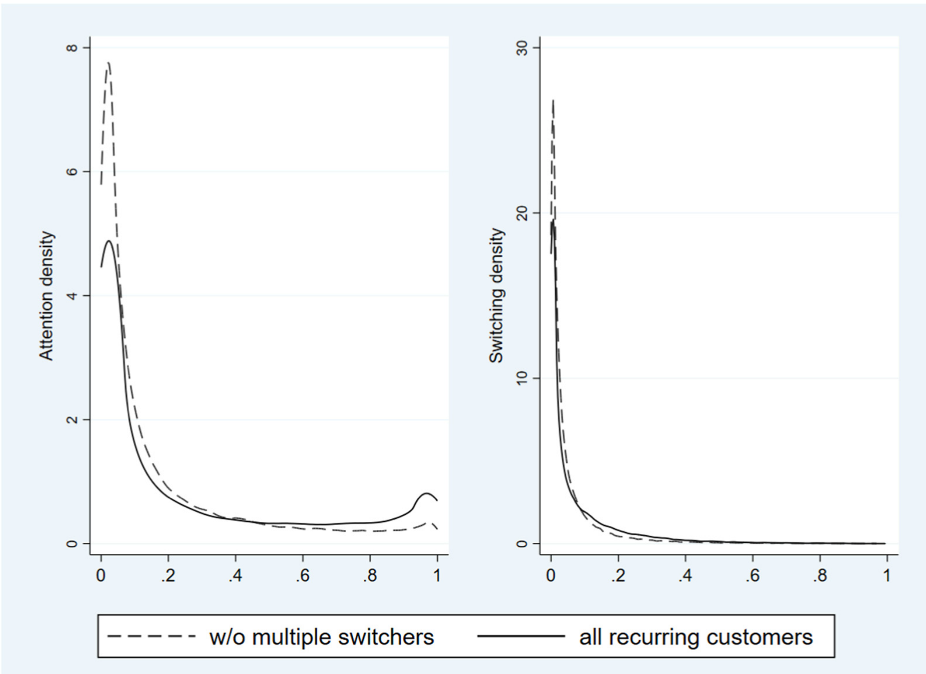

Fig. 5. Kernel distribution of the predicted probability of paying attention and predicted probability of switching.
Notes: Kernel density functions of predicted probability of attention (left) and predicted probability of switching (right). Density functions are presented for the sample excluding multiple switchers (dashed line) and for the total sample of recurring customers (solid line).

Our final check used the 2014 change in car insurance legislation, which increased customer incentives to pay more attention to their choice of insurance provider. Before 2014, customers involved in an accident that was not their fault were required to file their motor third-party liability insurance claims with the guilty party's third-party insurance provider, not their own. Since 2014, customers can file such claims with their own insurers for third-party liability claims up to a limit of €10,000. This aspect of the legislation change aimed to increase customer protection and awareness of product choice. We expect that customers were more price-sensitive before 2014. This quasi-experimental information helps to verify the extent to which our choice equation may be mis-specified or confounded by unobservables, given that the role of other factors beyond the offer price should be minimal before 2014.

5. Results and discussion

The two-step GMM estimates are plotted in Fig. 4, illustrating the percentage marginal effects (at mean values) for the attention and choice equations, respectively. The attention equation considers customers' past behavior and events, as well as the contemporaneous values of customer demography and car characteristics. The attention equation also includes a logarithmic time trend and a constant that is not depicted on the graph but is reported in Table 2. The choice equation contains contemporaneous value of the price of the chosen offer and the years elapsed since the insurance provider was first established in the Estonian insurance market.

Customer attention decreases as their tenure with the same insurance provider increases, as well as with the insured car's value. Customer consideration increases with increasing car engine power. To a lesser extent, the absolute and relative prices of past offers positively influence customer attention over the following period. Additionally, the customers who had filed claims and chosen lower deductibles were more likely to pay attention. Interestingly, automatically generated offers in the previous period correlated with higher customer attention in the following year. Customer demographics have a modest effect on attention. Females are more likely to pay attention than men. People living in cities also pay slightly less attention to insurance terms than those living in a non-urban environment, which is intuitive, given the higher dependency on cars in rural and remote areas. The consumer age effect is small but positive, meaning that older customers are more likely to pay attention.

As expected, the choice is negatively related to the price of the offer. For each 1 % increase in the offer price, the likelihood of the customer switching to that offer drops by 1.7 %. There is a very small but precisely estimated effect indicating that customers prefer to switch to offers from insurance providers who have a more established brand in the market. This result is in alignment with Honka et al. (2017) showing that bank brand awareness shifts the utility of retail banks customers only marginally. Therefore, should a consumer pay attention to their renewal offer, their choice between insurance offers is predominantly price-driven and modestly tilted towards providers with more established brands.

The sample of younger customers provides parameter estimates that are weaker in magnitude. The parameter estimate for the price offer in the choice equation is substantially lower at −0.52 %, and the brand estimate is 0.002 %. These findings suggest that younger customers (or new customers) are less price-sensitive (Table 2).

The densities for predicted attention and predicted switches as shown on Fig. 5 are highly right-skewed. This skew is less pronounced for attention probability, which exhibits a slightly multi-modal pattern. The sample including multiple switchers is less skewed and shifts both attention and switching towards higher probabilities. As expected, multiple switchers are more likely to pay attention and to switch.

The predicted attention probability, which varies in terms of consumer characteristics and policy renewal terms, has a strong decay effect (see Fig. 6), with a mean 32 % attention rate at the time of the first policy renewal. This is down by almost 16 % by the third year

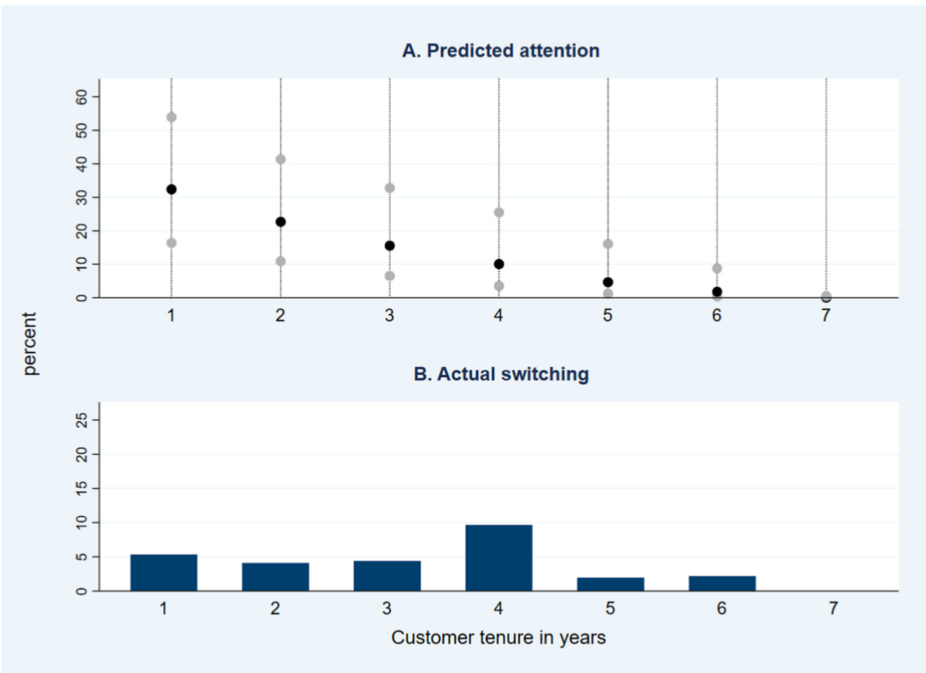

Fig. 6. Predicted probabilities of attention and brand switching by customer tenure.
Notes: A. Predicted probability of attention (in percentage terms) by the number of years with the same insurance provider, mean values with 95 % confidence intervals. Panel B: Mean actual switching rate by the number of years with the same insurance provider. Sample of all recurring customers, including the multiple switchers.

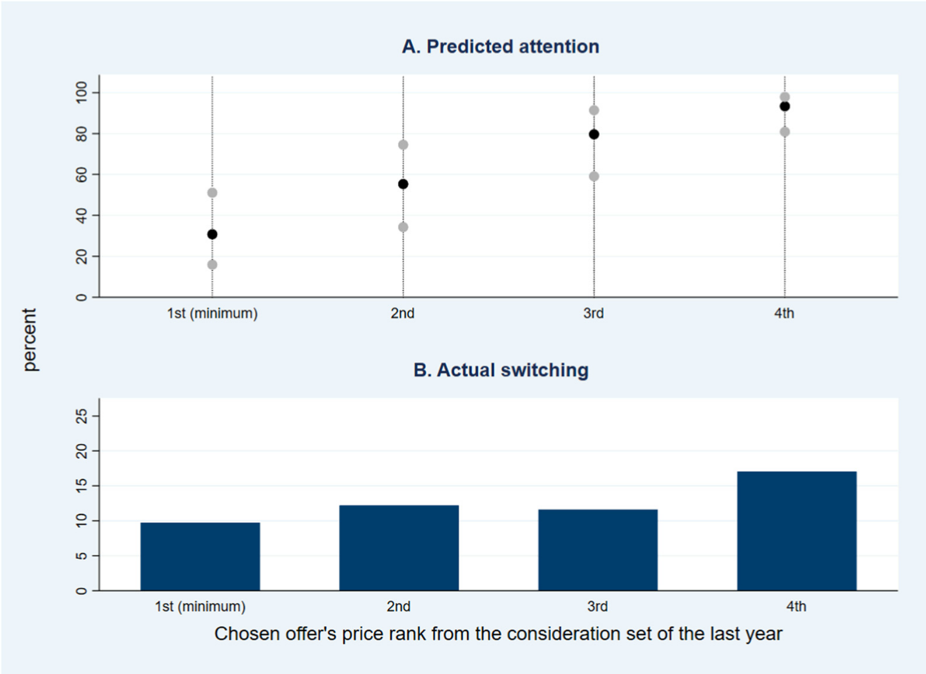

Fig. 7. Predicted probabilities of attention and customer switching by the relative price of the last chosen offer.
Notes: A. Predicted probability of attention (in percentage terms) by the price rank of the last chosen offer, mean values with 95 % confidence intervals. Panel B: Mean actual switching rate by the price rank of the last chosen offer. Sample of all recurring customers, including the multiple switchers.

and by about 2 % after the sixth year of renewal. Our predicted attention probabilities fit well into the attention estimate range provided by Gabaix (2019) across 11 cross-sections of studies in varying contexts, with a mean value of 44 % and 28 % standard deviation. The actual switching rate peaks at 10 % in the fourth year of renewal and drops sharply thereafter. There is no one-to-one relationship between attention and switching rates over the customer tenure. In the first two years of renewal, fewer than 20 % of customers who pay attention also switch. By the third year of renewal, almost one-third of customers who are paying attention also switch, and by the fourth year, this percentage reaches as high as 96 %. This suggests that while customer incentive to check on their renewal terms drops over their tenure with the same insurance provider, the propensity to switch, conditional on attention, grows. Hence, paying attention is worthwhile after staying with the same provider for many years, as it leads to action with considerable probability.

Customer attention also strongly depends on the relative price offer from the previous year (see Fig. 7). The higher the relative price of the chosen offer with respect to the alternative offers the more likely the customer is to pay attention to the renewal terms the following year. This shows that customers re-evaluate their past decisions and take actions during the next period to correct their choices and avoid recurring losses. This learning effect is stronger the more costly the inertia (the higher the chosen offer price relative to the alternative offers) from the previous period. The proportion of switchers among those customers who paid attention decreases the higher the gap with respect to the minimum price offer, indicating that customers who have chosen any offer other than the minimum price offer may have considerations other than cost informing their decision to favor a higher-priced offer.

The mean predicted probability of switching is 5.4 % and 7.7 % in a sample without and with multiple switchers; this matches well the observed proportion of switches (5.5 % and 7.8 %, respectively). The mean prediction for unobserved attention is 18.1 % in a sample of single switchers and 25.6 % in the full sample. This implies that, on average, in both samples, 30 % of consumers who pay attention also switch. The equivalent rate of switchers across samples proves the importance of customer heterogeneity at the attention decision stage but not at the choice decision stage, where the main decision factor is the price, given the consideration set offered to the customer. This finding aligns with experimental evidence of heterogeneous search behavior (Schunk and Winter, 2009).

Consistent with Honka (2014), we learn that high consumer inertia predominantly arises from inattention. However, our predicted switching rates remain lower relative to those in Honka's study. Honka (2014) reports a 60 % switching rate in the US car insurance market after eliminating search costs. Heiss et al. (2021), based on US Medicare Part D, found that the proportion of customers switching increased to 69 % when clients were forced to pay attention to selecting their healthcare plan. These differences can be attributed to our empirical context differing from that of Honka (2014) and Heiss et al. (2021), where the casualty and collision insurance we investigate is an ancillary financial service to the car leasing, which is the customer's primary financial service. According

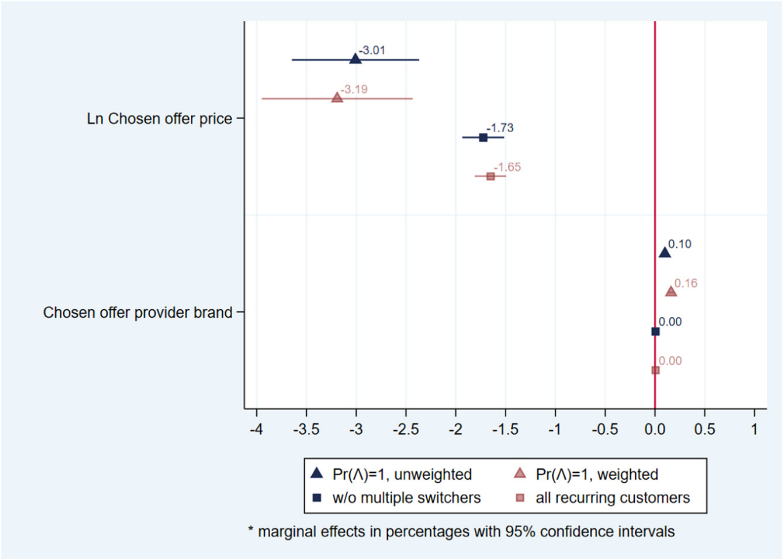

Fig. 8. Estimated marginal effects in percentages for the choice equation in the samples with incomplete and full attention, i.e., Pr(Attention)=1.

to Lipnowski et al. (2020), more complex search settings involve higher information processing costs, which imply greater consumer inattention.

Our robustness study (see Table 3 and Fig. 8) estimated the proportion of customers who had to pay attention because of a change in policy conditions (deductibles) or for other reasons. The switching rate of these customers is 23 %, which is even lower than the predicted switching rate of 30 % for customers whose attention probability had to be estimated. This indicates that our estimated switching rates conditional on attention are not downward biased but reflect the particularities of the market under study.

For our robustness checks, we conducted three exercises to address the identification of the attention and choice stages of the model. First, we exploited information about lessees who need to pay attention because their insurance terms (e.g., deductible rate) have changed (see also Heiss et al., 2021 for a resembling approach). The estimations on this subsample enable us to ascertain the reliability of our attention equation specification.

The second robustness check considered younger lessees, who are unlikely to have previous claims experience and therefore no state-dependent brand preference for any of the panel insurers. Since the identification of the choice stage hinges on the “push” assumption or that the customer has no predetermined preferences for specific insurance providers, the subsample of younger and less experienced consumers enables us to check for that condition. It also helps determine whether and to what extent the unobservables related to left-censoring (we did not observe customers’ events and decisions prior to 2010) might confound our results.

Finally, we used exogenous variation from a change in legislation that modified the rules of handling the Motor Third-Party Liability claims. This change, in effect since 2014, increased consumers’ incentives to pay attention to their insurance provider’s claim handling policies and practices.[9] Using this exogenous variation, we can verify the specification of our choice equation and determine how the different incentive schemas affected consumers’ attention.

The estimates for the price of the chosen offer and the brand carry similar signs but have higher magnitudes. The estimates on log price are only marginally larger than those from the wider sample. Differences in brand estimates are more substantial, although in absolute size, the brand effect remains very low—one additional year since brand establishment increases the choice probability by 0.09–0.156 % in the sample of individuals paying attention compared to 0.006–0.008 % in the total sample.

Finally, we analyzed the effects of motor insurance legislation changes that were issued and came into effect in 2014. The results were calculated for a subsample of observations prior to 2014, for the sub-sample of customers observed in 2014 and observed after 2014, and for the subsample of all customers observed and not observed in 2014 (see Table 4 andFig. 9 below).

[9] After 2014, the regulation stipulated that customers must submit third-party-induced insurance claims to their selected insurance provider if the claim is below € 10,000 and there is no dispute about the party at fault. Prior to 2014, third-party-induced claims were always filed by the insurance provider of the party at fault. In our setting, the choice of the third-party insurer is in fact independent of the choice of Own Damage insurer; however, since customers make both choices jointly in the sample template provided by the insurance broker, we suspect that this change in the claims handling procedure has affected consumer choice considerations more generally.

Table 4
Marginal effects at the mean for the samples before and after the 2014 legislation changes.

Probability of switching the insurance provider	After 2014		Before 2014
	All customers	Only customers from before 2014	
1st stage: Decision to pay attention			
Lag ln price of last offer	0.01613***	0.01733***	0.02102***
	(0.00146)	(0.00182)	(0.00180)
Price rank of last offer	0.00364***	0.00462***	0.00722***
	(0.00029)	(0.00039)	(0.00061)
Lag deductible, low	0.00216	0.00107	0.01181***
	(0.00153)	(0.00177)	(0.00316)
Ln car value	−0.00618***	−0.00818***	−0.00409**
	(0.00052)	(0.00071)	(0.00126)
Ln engine power	0.00380**	0.00216	0.01059***
	(0.00129)	(0.00143)	(0.00240)
Lag count claims: Self	0.00060*	0.00007	0.00075
	(0.00035)	(0.00043)	(0.00122)
Lag count claims: Third	0.00188***	0.00131**	0.00086
	(0.00041)	(0.00048)	(0.00148)
Lag count claims: Other	0.00107***	0.00072**	−0.00038
	(0.00021)	(0.00027)	(0.00081)
City/Urban	−0.00066*	0.00011	−0.00081
	(0.00036)	(0.00047)	(0.00068)
Age	0.00013***	0.00012***	0.00014***
	(0.00002)	(0.00003)	(0.00004)
Female	0.00199***	0.00178***	0.00383***
	(0.00040)	(0.00051)	(0.00082)
Log year trend	0.01288***	0.01611***	0.00593***
	(0.00178)	(0.00248)	(0.00162)
2nd stage: Choice decision			
Ln price of chosen offer	−0.01876***	−0.02010***	−0.03486***
	(0.00156)	(0.00184)	(0.00330)
Brand of chosen provider	0.00005**	−0.00000	0.00000
	(0.00002)	(0.00003)	(0.00004)
Observations	32,471	20,519	14,997
Customers	14,476	8018	8662
GMM-criterion	0.00361	0.00187	0.00459
Mean predicted attention	0.16455***	0.18818***	0.21126***
	(0.00123)	(0.00167)	(0.00189)
Mean predicted switch	0.04632***	0.05146***	0.07395***
	(0.00117)	(0.00154)	(0.00214)
Mean of actual switchers	0.04443***	0.05031***	0.07222***
	(0.00038)	(0.00049)	(0.00078)

6. Summary and conclusions

Building on the two-stage model developed by Hortaçsu et al. (2017), this study found considerable consumer inertia and inattention in car insurance among car leasing customers in a competitive market with very low switching costs for the consumer. The insurance distribution system we observed features high transparency and substantially lowered information processing costs for the consumer. Nevertheless, in alignment with Honka (2014), we observed considerable inattention, which may suggest further behavioral frictions beyond information-processing costs. More than three-quarters of customers who switch end up with the lowest price offer from their choice set, while only 54 % of non-switchers renew at the minimum price of their set of offers. Consumers who switch pay nearly 15 % lower premiums with the new provider compared to the offer from their past provider. Those who stay with their incumbent provider renew at a price that is on average 6 % lower than the previous year's offer, while the switching customers pay 13 % less compared to the previous year's offer.

Predicted attention has a right-skewed distribution, with the mean ranging between 18 % and 26 %, depending on whether only single or multiple switchers are considered. Of consumers who pay attention, 30 % decide to switch. Attention is highly heterogeneous and depends on customer tenure, individual preferences, and background characteristics. The results for the subsample of customers under 34 years old and with no previous switching history align well with the predicted ranges for the broader samples. This proves that our results are not biased by unobserved state dependencies and left censoring. Additionally, the results for the subsample of customers who paid attention suggest that the outcomes from the two-step model are plausible and likely to be at the lower boundary of the true parameter estimates. The robustness checks using changes in car insurance legislation prove that our results agree with the underlying rationale and maintain estimates in plausible ranges.

Conditional on the consumer deciding to consider alternative offers, price is a very strong determinant of consumer choice. Insurance provider brand has a weak positive effect on consumer choice. None of the choice decision factors differ between the groups of single switchers and the more experienced multiple switchers. This indicates that the learning effect is manifested in the decision's

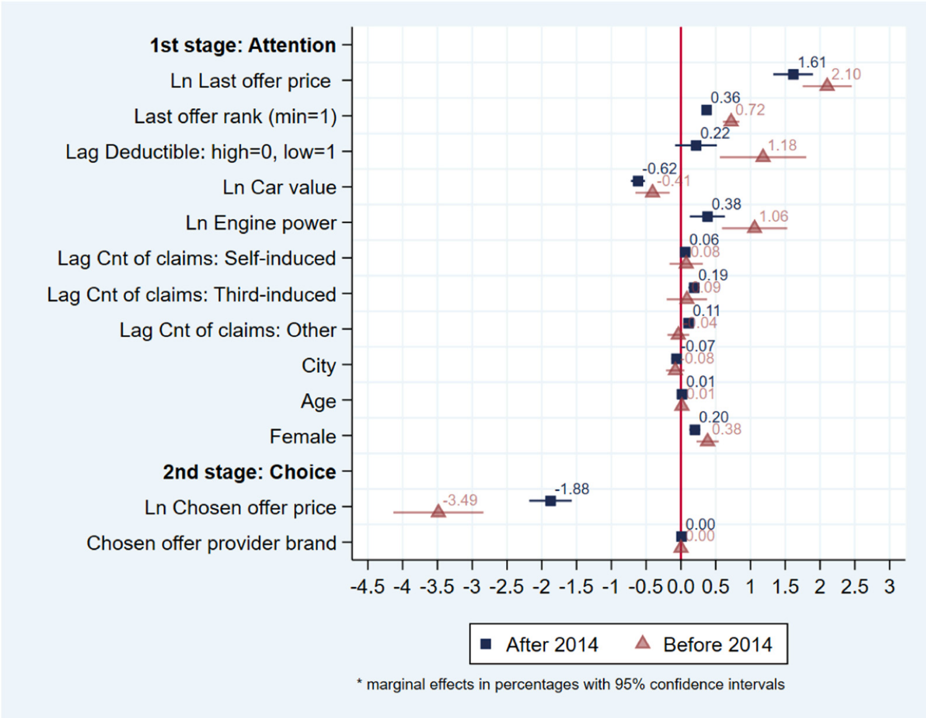

Fig. 9. Estimated marginal effects in percentages of the samples before and after the 2014 legislative changes.

attention state and is irrelevant to the choice decision. Time trends exhibit a modest increase in consumers' propensity to pay attention, which may be a positive signal of improving customer awareness. Whether this trend continues and is related to increased financial literacy, openness, transparency, and competitiveness in the insurance market remains to be seen. Further studies could pursue these avenues of investigation.

Declaration of competing interest

Kaido Kepp reports a relationship with IIZI Kindlustusmaakler AS that includes: board membership. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2025.107233.

Data availability

The authors do not have permission to share data.

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Appendix 4

Online Supplementary material to Article III. Supplement A

Table A1: Summary statistics

Customer segments	Retention	Single switch	Multiple switches	Total
Frequency	32 968	14 465	4 911	52 344
Years with the same provider				
Mean	2,0129	1,7501	1,4103	1,8837
StDev	(1.0848)	(1.0762)	(0.9391)	(1.0865)
Chosen price rank 1-5: min=1				
Mean	1,5578	1,6852	1,6630	1,6029
StDev	(0.9136)	(1.0157)	(0.9985)	(0.9528)
LWhichDeductible				
Mean	0,9664	0,9561	0,9440	0,9614
StDev	(0.1803)	(0.2049)	(0.2299)	(0.1926)
Car value in thous €				
Mean	14,7507	14,2939	15,6722	14,7109
StDev	(7.0047)	(7.6789)	(9.2243)	(7.4374)
lnEnginePower				
Mean	4,5523	4,5700	4,6067	4,5623
StDev	(0.2431)	(0.2419)	(0.2424)	(0.2433)
No of past claims: Self				
Mean	0,1152	0,1783	0,2199	0,1424
StDev	(0.3747)	(0.5069)	(0.5652)	(0.4368)
No of past claims: Third				
Mean	0,0856	0,1558	0,1613	0,1121
StDev	(0.3354)	(0.4503)	(0.4607)	(0.3847)
No of past claims: Other				
Mean	0,2601	0,4750	0,5952	0,3509
StDev	(0.6390)	(0.9466)	(1.1000)	(0.7958)
City: Yes(1), No(0)				
Mean	0,5379	0,4962	0,5085	0,5236
StDev	(0.4986)	(0.5000)	(0.5000)	(0.4994)
Age				
Mean	43,9473	44,1135	43,8681	43,9858
StDev	(11.1277)	(10.8083)	(10.6531)	(10.9965)
Female: Yes(1), No(0)				
Mean	0,3802	0,3868	0,3376	0,3780
Price of chosen offer				
Mean	390,0416	402,9585	421,0950	396,5246
StDev	(136.8416)	(154.1252)	(161.2160)	(144.5358)
Years since brand establishment				
Mean	8,8339	8,8411	9,4197	8,8908
StDev	(5.2489)	(5.7065)	(5.8853)	(5.4432)
Provider's no of customers				
Mean	1926,1856	1955,1702	1822,4425	1924,4620
StDev	(715.4454)	(786.0990)	(761.0078)	(740.7480)

Notes: Mean values (proportions for discrete variables) and standard deviations in parentheses.

Online Supplementary material to Article III. Supplement B
Insurance offer form with illustrative pseudo-values

The Lessor has requested this insurance proposal based on following insurable interest

Lessee: ABC DE
Personal ID/registration code of the lessee: **12345678**
Policyholder:
Owner of the vehicle:
Vehicle: **Honda Civic**
First registration year: **2017**
Engine power: **100 KW**
Insured value: **Market Value** in Estonia (including value added tax)

Insured risks: road accident, natural disaster, fire, vandalism, theft, robbery, glass damage, New Value Cover
Usage type: passenger car (ordinary usage)
Territorial validity: Europe excl CIS
Additional equipment is insured as per inspection protocol or sales proposal. For more details about indemnification limits see comparison table of insurance covers

In case the minimum requirements set out in the proposal requested by the Lessor are not in line with the planned usage conditions of the vehicle, i.e. lessee as a person liable for the loss or damage of the vehicle wants to extend the insurance cover to additional risks, please inform our insurance broker using the contact details on the proposal latest within 3 days.

The insurance proposal to the Lessor is valid until DD.MM.YYYY

MOTOR OWN DAMAGE INSURANCE. Option 1					
	Salva	**PZU**	**Compensa**	**Seesam**	**ERGO**
Deductible	€200	€200	€200	€190	€190
Annual premium	€ 497.43	€ 517.92	€523.26	€544.66	€ 561.57

MOTOR OWN DAMAGE INSURANCE. Option 2					
	Salva	**PZU**	**Compensa**	**Seesam**	**ERGO**
Deductible	€300	€300	€300	€315	€300
Annual premium	€ 460.37	€ 462.60	€ 471.23	€ 479.51	€ 483.12

Online Supplementary material to Article III. Supplement C
Calculation of marginal effects

The marginal effects at mean values, standard errors, and 95% confidence intervals are calculated using the STATA command .nlcom.

The formula for calculating the marginal effects for the variables x_a in the attention equation is given in equation C.1.

$$\frac{d}{dx_a} = \beta_{x_a} \cdot \frac{\exp(z_1)\cdot\exp(z_{20})}{[\exp(z_1)+1]^2\cdot[\exp(z_{20})+\exp(z_{21})+\exp(z_{22})+\exp(z_{23})+\exp(z_{24})]} \qquad \text{(C.1.)}$$

where z_1 is the linear index of 14 variables and a constant term from the binary logit specification of the attention equation in the first stage of the model. $z_{20}, \ldots, z_{24}$ are the linear indices from the choice equation in the second stage and include two variables but no constant term. Hence, z_{20} is the linear combination for the chosen offer, and the indices $z_{21}, \ldots, z_{24}$ refer to the linear combinations of the first, second, third, and fourth alternative offers, respectively. Note that according to the conditional logit specification, the linear indices in the choice equation vary only with respect to the variable terms, whereas the parameter terms remain equivalent.

The marginal effects for the choice equation variables x_c are retrieved according to equation C.2.

$$\frac{d}{dx_c} = \beta_{x_c} \cdot \frac{\exp(z_1)\cdot\exp(z_{20}) \cdot [\exp(z_{21})+\exp(z_{22})+\exp(z_{23})+\exp(z_{24})]}{[\exp(z_{20})+\exp(z_{21})+\exp(z_{22})+\exp(z_{23})+\exp(z_{24})]^2\cdot[\exp(z_1)+1]} \qquad \text{(C.2.)}$$

For the sample with full attention, or where Pr(Attention)=1, the marginal effects for the choice equation variables x_c are calculated according to equation C.3.

$$\frac{d}{dx_c} = \beta_{x_c} \cdot \frac{\exp(z_{20}) \cdot [\exp(z_{21})+\exp(z_{22})+\exp(z_{23})+\exp(z_{24})]}{[\exp(z_{20})+\exp(z_{21})+\exp(z_{22})+\exp(z_{23})+\exp(z_{24})]^2} \qquad \text{(C.3.)}$$

Curriculum Vitae

Personal data

Name:	Kaido Kepp, ORCID 0000-0003-4105-0285
Date of birth:	02.01.1974
Place of birth:	Estonia
Citizenship:	Etonian

Contact data

E-mail:	kaido.kepp@taltech.ee

Education

2016-2026	Tallinn University of Technology, PhD candidate
1996-1999	University of Tartu, M.A.
1992-1996	University of Tartu, B.A.
1981–1992	Jõgeva Secondary School No 2

Language competence

Estonian	Native
English	Fluent
German	Fluent
Russian	Fluent

Professional employment

2018–	IIZI Kindlustusmaakler AS, CFO, Member of the Management Board
2018-2024	Kredex Krediidikindlustuse AS, Member of the Supervisory Board
2016-2018	IIZI Kindlustusmaakler AS, Member of the Supervisory Board
2010-	Tallinn University of Technology, part-time lecturer
2007-2014	Royal&SunAlliance Insurance Group, CEO Estonia (Country Manager), Member of the Supervisory Board of AAS Balta (Latvia) and UAB Lietuvos Draudimas (Lithuania)
1999-2007	ERGO Insurance Group. Member of the Management Board for ERGO Life in Estonia (since 1999), for all ERGO Life and non-life companies in the Baltics since 2004 responsible for Life, Pensions and Investment
1996-1999	ERGO Insurance Group. Life insurance underwriter in Estonia

Courses

2019	The Economics of Insurance Markets, Florence School of Banking and Finance. Instructor: Professor Ralph Kojien, University of Chicago, Booth School of Business
2018	Long Panel Data Models. Instructor: Professor T. Malinen, University of Helsinki

Teaching and supervising at TalTech

Courses	Corporate Finance (Compulsory in Finance Master Programme) Risk Management (Elective in Finance Master Programme)
Supervising	over 50 successfully defended Master Thesis and numerous Bachelor Thesis

Elulookirjeldus

Isikuandmed

Nimi:	Kaido Kepp, ORCID 0000-0003-4105-0285
Sünniaeg:	02.01.1974
Sünnikoht:	Eesti
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Kontaktandmed

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Hariduskäik

2016-2026	Tallinna Tehnikaülikool, doktorantuur
1996-1999	Tartu Ülikool. M.A.
1992-1996	Tartu Ülikool, B.A
1981-1992	Jõgeva 2. Keskkool, keskharidus

Keelteoskus

Inglise keel	kõrgtase
Saksa keel	kõrgtase
Vene keel	kõrgtase

Teenistuskäik

2018–	IIZI Kindlustusmaakler AS, finantsjuht, juhatuse liige
2018-2024	Kredex Krediidikindlustuse AS, nõukogu liige
2016-2018	IIZI Kindlustusmaakler AS, nõukogu liige
2010-	Tallinna Tehnikaülikool, lektor (osakoormusega)
2007-2014	Royal&SunAlliance Insurance Group, Eesti tegevjuht, nõukogu liige AAS Balta (Läti) ja UAB Lietuvos Draudimas (Leedu)
1999-2007	ERGO Insurance Group. Juhatuse liige Ergo Elukindlustuse AS (alates 1999), ja kõikides ERGO elu- ja kahjukindlustusseltsides alates 2004, vastutusala elu- ja pensionikindlustus, investeeringud
1996-1999	ERGO Elukindlustuse AS riskijuht, kindlustusosakonna juhataja

Täiendõpe

2019	The Economics of Insurance Markets, Florence School of Banking and Finance. Instructor: Professor Ralph Kojien, University of Chicago, Booth School of Business
2018	Long Panel Data Models. Instructor: Professor T. Malinen, University of Helsinki

Õppetöö ja juhendamine Tallinna Tehnikaülikoolis

Kursused	Ettevõtte rahanduse süvakursus (kohustuslik kursus ärirahanduse magistriõppes) Riskijuhtimine (valikkursus ärirahanduse magistriõppes)
Juhendamine	eduka katsmiseni juhendatud üle 50 magistritöö ja mitmeid bakalaureusetöid

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