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Faculty of Business Economics

Master of Management

Master's thesis

Financial underperformance and firm innovation: an empirical study for Flemish firms

Marjaneh Ghafari
Th Bich Ngc Nguyn

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Strategy and Innovation Management

SUPERVISOR :
Prof. dr. Bart LETEN

MENTOR :
Mevrouw Lily-Anne HONS

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www.uhasselt.be
Universiteit Hasselt
Campus Hasselt:
Martelarenlaan 42 | 3500 Hasselt
Campus Diepenbeek:
Agoralaan Gebouw D | 3590 Diepenbeek

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ACKNOWLEDGEMENTS

First and foremost, we would like to express our deepest gratitude to our thesis supervisor, Prof. Dr. Bart Leten, for his continuous guidance, constructive feedback, and encouragement throughout this research process. His expertise in strategic management and innovation, combined with his ability to challenge our thinking, has been invaluable in shaping both the academic rigor and practical relevance of this thesis.

We are equally grateful to our mentor, Ms. Lily Ann Hons, for her insightful advice, thoughtful suggestions, and constant support. Her perspective helped us refine our research focus and strengthen the quality of our analyses.

We would also like to sincerely thank our family and friends for their unwavering emotional support and understanding during the intense periods of writing and data analysis. Their encouragement has been a constant source of motivation.

Lastly, we acknowledge the use of ChatGPT as a writing tool, which assisted us in drafting and refining this document. All ideas, interpretations, and analyses are entirely our own, developed through our studies and research. ChatGPT was solely used to support the writing process and did not contribute to the academic content, findings, or conclusions of this work.

Thank you to everyone who has been part of this journey. Your support has made this thesis possible.

ABSTRACT

This study examines how financial underperformance relative to aspiration levels influences firm innovation, distinguishing between historical aspirations (HA) and social aspirations (SA). Drawing on the Behavioral Theory of the Firm and the Threat–Rigidity perspective, we investigate whether the relationship follows a positive, negative, or nonlinear pattern, and whether firms respond more strongly to one aspiration type. Using a balanced panel of 9,951 Flemish firms from 2014–2019, innovation output is measured as the combined log-transformed count of patents and trademarks, while underperformance intensity is calculated relative to HA and SA using lagged return on assets. Pooled OLS models with cluster-robust standard errors test both linear and quadratic specifications to capture potential curvilinear effects. The results reveal that underperformance relative to HA exhibits a significant positive linear association with innovation output, consistent with problemistic search predictions. In contrast, underperformance relative to SA shows an asymmetrical U-shaped relationship: severe deficits stimulate innovation, while mild deficits are associated with reduced innovation, reflecting a mix of competitive motivation and reputational caution. Comparative analysis indicates that firms react more consistently to historical performance gaps, while responses to social benchmarks depend on gap severity. These findings contribute performance feedback theory by showing that the source and magnitude of performance gaps jointly shape innovation behavior. Managerially, they highlight the need to tailor innovation strategies to the nature of underperformance signals, leveraging historical trends for early intervention and calibrating responses to peer-based gaps according to their intensity.

LIST OF ABBREVIATIONS

BTOF	Behavioral Theory of the Firm
CI	Confidence Interval
CR2	Cluster Robust Standard Errors (version 2)
FE	Fixed Effects
GVIF	Generalized Variance Inflation Factor
HA	Historical Aspiration
OLS	Ordinary Least Squares
ROA	Return on Assets
RQ	Research Question
SA	Social Aspiration
SME	Small and Medium sized Enterprise
UIH	Underperformance relative to Historical aspirations
UIS	Underperformance relative to Social aspirations
ZINB	Zero Inflated Negative Binomial

FINANCIAL UNDERPERFORMANCE AND FIRM INNOVATION: AN EMPIRICAL STUDY FOR FLEMISH FIRMS.

CHAPTER 1: INTRODUCTION

1.1 Research motivation

In today's highly competitive and rapidly changing business environment, innovation is no longer an optional activity—it has become essential for sustaining growth, competitiveness, and long-term survival. Firms that innovate are better positioned to respond to technological changes, shifting market demands, and evolving customer preferences. However, innovation involves significant uncertainty and resource commitment, making it a risky choice, particularly when a firm's financial performance falls below expectations.

In practice, managers evaluate performance by comparing current results to benchmarks, which can be drawn from their firm's own historical records or from the performance of industry peers. These benchmarks are more than simple metrics—they shape how performance shortfalls are perceived and interpreted. A decline relative to past performance may be seen as a signal to improve internal processes, while a shortfall relative to competitors may raise reputational concerns and intensify competitive pressure.

Despite the strategic importance of such interpretations, there is limited systematic evidence on how firms adjust their innovation activities under financial underperformance, and whether responses differ depending on the chosen benchmark. Understanding these dynamics is particularly relevant in regions such as Flanders, where innovation is central to economic growth and firms operate in markets characterized by both strong local competition and exposure to international pressures.

1.2. Problem statement

While innovation is widely recognized as a driver of firm performance, the decision to innovate under conditions of financial underperformance is complex and not fully understood. Existing studies provide mixed and sometimes contradictory findings: in some contexts, underperformance stimulates innovation as firms search for solutions to close performance gaps; in others, it discourages innovation due to heightened risk aversion.

In addition, the relative influence of different aspiration reference points—historical versus social—remains unclear. Historical benchmarks may trigger quicker, internally focused responses, whereas social benchmarks may generate stronger and more persistent pressure through competition and reputation. Yet, the evidence on which type of benchmark drives stronger innovation responses is inconsistent, and much of the existing research focuses on specific industries or time periods, limiting the generalizability of findings.

These gaps hinder both theory and practice. Academically, they prevent a clear understanding of the conditions under which underperformance leads to innovation or conservatism. For managers, they make it harder to interpret performance signals and decide when innovation is an appropriate strategic response. This study addresses these issues by examining, in a large-scale and multi-industry context, how financial underperformance relative to different aspiration benchmarks influences firm innovation, and whether the severity of the performance gap alters these effects.

CHAPTER 2: LITERATURE REVIEW

This chapter presents the theoretical and empirical basis of the study. It explores the Behavioral Theory of the Firm (BTOF) as the primary framework for understanding how firms react to financial underperformance, alongside the Threat-Rigidity Hypothesis to highlight the circumstances that restrict adaptive behavior. Additionally, the chapter reviews research on performance feedback and innovation, focusing on how the severity of underperformance and sources of aspiration—historical (HA) versus social (SA)—influence managerial decisions and outcomes related to innovation.

2.1 Theoretical Foundations

This section presents the theoretical foundations of the study. The BTOF serves as the main framework, explaining how firms make decisions under bounded rationality, guided by performance feedback. The Threat-Rigidity Hypothesis is introduced as a complementary perspective that highlights psychological constraints when performance gaps are perceived as threats.

Behavioral Theory of the Firm as the Core Framework

Developed by Cyert and March (1963), BTOF describes organizational decision-making as an adaptive process constrained by bounded rationality. Firms compare actual performance against aspiration levels, which are set using either historical performance or industry peer benchmarks. When performance meets or exceeds aspirations, firms tend to maintain existing routines. When it falls short, the gap signals a problem and triggers problemistic search—a targeted search for solutions aimed at closing the gap.

Problemistic search unfolds sequentially: managers begin with familiar, low-risk options and, if these prove insufficient, progressively explore more distant and uncertain alternatives. This process is inherently dynamic and feedback-driven—decisions are influenced by prior outcomes, which in turn adjust aspiration levels and shape future choices. In the context of innovation, negative performance feedback can expand the scope of search to include riskier, more novel solutions, thereby increasing the likelihood of innovation.

Threat-Rigidity as a Complementary Perspective

While BTOF assumes that performance shortfalls prompt adaptive search, the Threat-Rigidity Hypothesis (Staw, Sandelands, & Dutton, 1981) offers a contrasting prediction. When managers perceive underperformance as a severe or survival-threatening condition, psychological stress can narrow their attention, limit information processing, and reduce the range of alternatives considered. In such situations, firms tend to fall back on established routines and adopt defensive, risk-averse strategies rather than exploring novel solutions. This perspective explains why underperformance does not always lead to the increased innovation predicted by BTOF, especially when threat perceptions dominate managerial decision-making.

2.2 Underperformance and Innovation

2.2.1 The Impact of Underperformance on Innovation

Innovation is a multifaceted phenomenon essential for firm survival, competitiveness, and long-term growth (Dodgson, Gann, & Phillips, 2014). It encompasses both technical and behavioral dimensions. On the technical side, it results in new or significantly improved products, processes, organizational methods, or business models (Organisation for Economic Co-operation and Development [OECD], 2005). On the behavioral side, it reflects a strategic process of search, experimentation, and adaptation to environmental challenges (Tushman & O'Reilly, 1996; Asare-Kyire, Bonsu, Appienti, & Ackah, 2023).

In addition to these dimensions, innovation can be viewed as an input–output process, in which firms mobilize resources—such as R&D investments, human capital, and organizational capabilities—to generate tangible outputs including patents, trademarks, and new products (Janger, J., Schmidt, T., Andries, P., Rammer, C., & Hollanders, M., 2017; Bello, Ravanos, & Smallenbroek, 2024). It is also an ongoing strategic activity shaped by managerial decision-making and external pressures (Kemp, Folkeringa, De Jong, & Wubben, 2003; Asare-Kyire et al., 2023). Because innovation is inherently uncertain—often involving ambiguous outcomes and delayed returns—managers' interpretations of environmental conditions and performance feedback play a critical role. These perceptions can determine whether firms commit to innovation or adopt more conservative strategies (Dodgson et al., 2014; Greve, 2003).

Linear relationship

The Behavioral Theory of the Firm (Cyert & March, 1963) frames underperformance as a trigger for *problemistic search*, prompting managers to explore new solutions to close performance gaps. When shortfalls are interpreted as challenges rather than existential threats, firms tend to increase risk-taking and innovation-related activities (Lucas, Knoben, & Meeus, 2018; Zhang, Gu, & Yang, 2024). Greve (2003) documents in the shipbuilding industry that moderate underperformance heightens managerial preference for risk, while Ren, Zeng, and Zhong (2024) show that low performance can increase exploratory innovation aimed at regaining competitiveness.

In contrast, the Threat–Rigidity Hypothesis (Staw, Sandelands, & Dutton, 1981) predicts that underperformance can narrow managerial attention and induce risk-averse behavior. This occurs when shortfalls are perceived as severe threats to survival or legitimacy. Audia and Greve (2006) find that vulnerable firms—particularly SMEs—often adopt conservative strategies that reduce innovation. Similarly, Zhong, Chen, and Ren (2022) show that performance pressure can push firms toward low-risk, cost-efficient strategies with faster returns (Guo & Ding, 2017; Fu, Liao, Liu, & Lu, 2021). Defensive reactions may also be driven by concerns about managerial reputation or legitimacy (Chen, Zhong, & Lv, 2022). Lucas et al. (2018) further note that managerial interpretations are influenced by cognitive biases, leading to selective attention to negative cues, which can reinforce cautious behavior.

Beyond motivation, the translation of underperformance into innovation depends on resource availability. Slack resources influence whether firms can act upon the search motives triggered by performance gaps (Todeva, 2007; Gavetti et al., 2012). Lu and Wong (2019) find that high slack can weaken the urgency created by underperformance, whereas low slack can intensify search, consistent with Hewitt-Dundas's (2006) view that scarcity heightens responsiveness. In contrast, Huang, He, and Yang (2021) report that greater slack can facilitate the financing and implementation of innovation projects. Firm size, a proxy for resource endowment, shows similar patterns: larger firms are more likely to sustain or increase innovation during underperformance (Audia & Greve, 2006), with both innovation effort and productivity scaling positively with size (Knott & Vieregger, 2018). SMEs, by contrast, often focus on incremental rather than radical innovations (Oke, Burke, & Myers, 2007), which may deliver faster returns in high-technology sectors.

Nonlinear relationship

An emerging stream of research integrates the Behavioral Theory of the Firm (BTOF; Cyert & March, 1963) and the Threat–Rigidity Hypothesis (Staw, Sandelands, & Dutton, 1981) into nonlinear models to explain heterogeneous innovation responses to underperformance. These studies highlight that underperformance does not produce uniform effects; instead, its impact depends on both the magnitude and duration of performance gaps (Ref & Shapira, 2017; Yu, Minniti, & Nason, 2019; Liu, Song, Lai, & Xie, 2024).

Empirical evidence consistently identifies an inverted U-shaped relationship (Ref & Shapira, 2017; Liu et al., 2024). At moderate levels of underperformance, managers interpret performance gaps as challenges, stimulating problemistic search and risk-taking consistent with BTOF (Greve, 2003; Ren, Zeng, & Zhong, 2024). However, as the gap widens, perceived threat intensifies, cognitive focus narrows, and managers reduce engagement in uncertain innovation activities, aligning with Threat–Rigidity predictions (Staw et al., 1981; March & Shapira, 1992). The turning point—where innovation responses begin to decline—varies across industries and contexts but generally occurs when survival concerns dominate (Ref & Shapira, 2017; Liu et al., 2024). At this stage, the aspiration goal gives way to the survival goal, prompting a strategic shift from high-risk innovation to low-risk, efficiency-oriented activities, a process March and Shapira (1992) termed "shifting focus."

Temporal dynamics further complicate this relationship. In the short run, the inverted U-shape appears robust: Yu et al. (2019) find that performance slightly below aspirations is associated with increased innovation, but innovation declines sharply when the shortfall is large. Su, Yu, Chen, and Hou (2023) observe a similar pattern for cooperative innovation, where moderate durations of underperformance promote collaboration, while prolonged durations initially dampen it due to heightened caution.

However, when underperformance persists, the trajectory can reverse. Liu et al. (2024) and Su et al. (2023) report that prolonged underperformance may trigger renewed innovation, producing a U-shaped relationship over longer horizons. This shift reflects the exhaustion of defensive strategies and the eventual necessity of risk-taking to restore competitiveness (Dodgson, Gann, & Phillips, 2014). Quantitatively, Liu et al. (2024) show that extended durations flatten the inverted U-curve, and beyond a threshold duration, the slope turns positive again.

Persistent underperformance can also generate external pressures that reshape strategic choices. Brouthers and Hennart (2007) show that firms may cut innovation in the early years but substantially increase it after several years, driven by sustained shareholder demands and the accumulation of technological capabilities needed for recovery. External stakeholders may frame innovation as a necessary turnaround strategy, altering managerial perceptions of risk–return trade-offs (Ref et al., 2024).

A complementary stream distinguishes risk-taking motivation from ability. While motivation tends to increase as performance shortfalls grow, ability declines with resource erosion; this mismatch yields an inverted U-shape in observed risk-taking (Ref et al., 2024). Over time, however, motivation can re-elevate near the survival point, helping reconcile the short-run inverted U with the longer-run U-shape when defensive actions fail (Liu et al., 2024). Evidence on the exploration–exploitation trade-off also varies by setting: in R&D internationalization, shortfalls increase the exploitation share, strengthened by market turbulence and weakened by technological turbulence (Zhong et al., 2021, 2022); under innovation performance shortfalls, firms increase exploratory emphasis, particularly where board monitoring and analyst coverage are stronger (Ren et al., 2024).

The literature shows conflicting evidence on how underperformance affects innovation. Some studies find a positive linear effect, consistent with the Behavioral Theory of the Firm, while others report a negative linear effect, in line with the Threat–Rigidity Hypothesis. A third stream identifies nonlinear patterns—typically an inverted U-shape, though in some long-term cases a U-shape emerges, highlighting the role of temporal dynamics. Findings on Slack are also mixed, with low Slack sometimes intensifying responsiveness and high Slack enabling project execution. Evidence on whether underperformance drives exploration or exploitation is similarly inconsistent and appears context-dependent. Finally, the role of external stakeholders in shaping innovation responses remains under-theorized. These contradictions highlight the need to examine, in a more general sense, how underperformance influences innovation on average across different contexts, abstracting from specific temporal, resource, or industry conditions.

2.2.2 Firm Sensitivity in the Context of Underperformance Relative to Aspiration Levels

Following the examination of how underperformance influences firms' innovation behavior, the discussion now turns to firm sensitivity in relation to aspiration levels. Particular attention is given to the distinction between historical and social aspirations, as these reference points may trigger different cognitive evaluations and strategic responses.

According to the BTOF, firms evaluate their performance against aspiration levels formed from both their own historical performance and comparisons with peers. Sensitivity to underperformance emerges through cognitive and behavioral responses—such as problemistic search, changes in strategy, and shifts in risk-taking. Subsequent research shows that historical and social aspirations can trigger these responses in systematically different ways (Greve, 2003; Baum & Dahlin, 2007).

For historical aspirations, underperformance is perceived as an internal issue, creating high short-term sensitivity due to the urgency of correcting performance deviations (Ye, Yu, & Nason, 2021). Greve (2003) indicates that in the Japanese shipbuilding industry, managers are sensitive to historical underperformance, quickly deploying internal improvement strategies, such as optimizing production processes, to restore performance. This sensitivity is particularly pronounced in small and medium-sized enterprises (SMEs), where survival pressure drives intrinsic risk-taking behavior, such as experimenting with new production methods Rosenbusch, Brinkmann, & Bausch, 2011 However, Chen and Miller (2007) note that this sensitivity diminishes when firms face bankruptcy risks, as cognitive focus shifts to asset protection, leading to defensive strategies like cost-cutting, which reduces risk-taking behavior. Su et al. (2023) add that prolonged historical underperformance initially increases growth pressure, promoting collaborative innovation strategies to improve performance. However, when survival pressure overtakes growth pressure over time, firms reduce innovation and adopt more conservative strategies (Hottenrott and Lopes-Bento, 2016).

In contrast, social aspirations heighten sensitivity through competitive pressure from industry peers, activating outward-oriented cognition and organizational strategies that are either collaborative or competitive (Kim & Lui, 2015). This is evidenced by Manzaneque, Rojo-Ramírez, Diéguez-Soto, & Martínez-Romero (2020), who find that Spanish SMEs are more sensitive to underperformance relative to industry benchmarks, leading to alliance strategies to share resources and mitigate competitive risks. Ye et al. (2020) emphasize that social feedback is more persistent due to inter-firm mobility barriers, causing firms in industries with high profit persistence to maintain long-term sensitivity, fostering risk-taking behavior such as developing competitive products. Su et al. (2023) indicate that prolonged social underperformance has a later inflection point for collaborative innovation compared to historical aspirations, as competitive pressure sustains growth motivation longer before survival pressure dominates, particularly in the biotechnology industry. Ahuja et al. (2008) add that strategic alliances enhance risk-taking behavior when firms are sensitive to social pressure, helping to reduce competitive uncertainty. However, Lucas et al. (2018) caution that sensitivity to social aspirations decreases when competitive pressure is negligible, leading to conservative strategies in small SMEs (Kemp et al., 2003).

Historical aspirations generate higher short-term sensitivity due to internal urgency but are easily disrupted by survival pressure, resulting in internal and less risky strategies (Lucas et al., 2018). This is empirically supported by Audia & Greve (2006), who find that underperformance relative to social aspirations leads to reduced risk-taking behavior, whereas the relationship is insignificant when comparing performance to historical aspirations. In contrast, social aspirations maintain more sustained sensitivity due to prolonged competitive pressure, promoting higher risk-taking through collaborative strategies Lyócsa, Výrost, & Baumohl (2018), Huang et al. (2021) show that historical aspirations are more sensitive to internal capabilities, while social aspirations depend on the competitive industry context. Janošová and Jirásek (2017) note that larger boards with older members reduce sensitivity to both aspirations, but the impact is stronger for social aspirations due to higher flexibility requirements. In the literature review, Gavetti et al. (2012) demonstrate that simple cognitive representations limit sensitivity to historical aspirations, leading to familiar strategies, while social aspirations activate broader cognition, albeit still boundedly rational.

Despite extensive research on how historical and social aspirations shape firm responses to underperformance, significant contradictions remain regarding their relative influence on risk-taking and innovation. Some studies find that underperformance relative to social aspirations reduces risk-taking, while the same effect is insignificant for historical aspirations (Audia & Greve, 2006). Others suggest the opposite, proposing that historical aspirations may induce less risky strategies due to internal performance pressures (Chen & Miller, 2007). These conflicting findings leave unanswered the question of which type of aspiration elicits stronger sensitivity.

The literature offers mixed evidence on whether firms are more sensitive to historical aspirations (HA) or social aspirations (SA). HA is often linked to stronger short-term reactions, as performance shortfalls are seen as urgent internal issues, especially in SMEs. Yet, this effect tends to fade when survival pressure dominates. SA, by contrast, is associated with more sustained sensitivity due to persistent competitive pressure, fostering collaboration or strategic alliances, though it can weaken in low-competition contexts.

This inconsistency creates a gap because prior studies often examine underperformance–innovation links within narrow settings—such as specific industries, firm sizes, or time horizons—making their findings context-dependent and difficult to generalize. Variations in research design, performance measures, and innovation indicators further hinder comparability. As a result, it remains unclear, on average, how strongly firms respond to underperformance across different contexts and which aspiration reference point tends to elicit a stronger innovation response.

2.3 Conceptual Framework and Hypotheses

Drawing on the reviewed literature, the following conceptual framework integrates insights from the Behavioral Theory of the Firm, the Threat-Rigidity perspective, and the Resource-Based View to explain how underperformance relative to aspiration levels influences firms' innovation behavior. Figure 1 illustrates the conceptual framework linking performance feedback to innovation via motivation, pressure, and risk orientation. This framework outlines the sequential process through which managers perceive and interpret performance gaps, and how these cognitive responses interact with the firm's capabilities to shape strategic action.

Aspiration levels may take different forms. Historical aspirations refer to internal benchmarks based on a firm's own past performance, while social aspirations are external benchmarks derived from competitors' performance. Signals based on internal benchmarks may be perceived as more familiar and adjustable, whereas signals based on external benchmarks are often tied to competitive standing and reputation, creating stronger pressure. Regardless of their source, both types of signals indicate a problematic decline, either in internal performance trends or in the firm's relative position in the market.

Following perception, managers interpret the signal. The Behavioral Theory of the Firm (BTOF) views underperformance as a challenge that stimulates problemistic search and increases the likelihood of innovation, suggesting a positive linear relationship between performance shortfalls and innovation. In contrast, the Threat-Rigidity perspective argues that underperformance is interpreted as a threat, leading to a narrowing of search, reliance on familiar routines, and reduced innovation, implying a negative linear relationship.

Building on these linear perspectives, recent research suggests that the magnitude of the performance gap can shift managerial attention from the aspiration goal to a survival goal. When the shortfall is moderate, firms are more likely to pursue innovation to close the gap. However, when it is severe enough to approach a survival point, managers may prioritize short-term stability over long-term exploration, resulting in reduced innovation. This shift forms the basis for conceptualizing nonlinear relationships between underperformance and innovation.

This integrated view highlights that underperformance can lead to either innovative or conservative responses, depending on how managers perceive and interpret performance gaps, whether their attention remains on aspiration goals or shifts toward survival. It also emphasizes that the reference point—historical versus social aspirations—may shape the salience of the performance signal and, consequently, the firm's behavioral sensitivity.

Research questions

These considerations lead to two central research questions for this study:

(1) How does financial underperformance relative to aspiration levels influence subsequent firm innovation, and is this relationship best characterized as positive, negative, or nonlinear?

(2) Do firms respond differently when underperformance is evaluated against historical benchmarks versus social benchmarks, and which type of aspiration elicits stronger sensitivity in shaping innovation behavior?

Building on the research questions, the following hypotheses translate the study's conceptual framework into empirically testable propositions. They specify the expected shape of the underperformance–innovation relationship (H1) and the comparative sensitivity to historical versus social aspirations (H2).

Hypothesis Development

H1: Underperformance influences firm innovation.

According to the BTOF, performance below aspirations is often interpreted as a challenge, triggering problemistic search and motivating firms to increase innovation in order to close the performance gap. This logic underpins H1a, predicting a positive relationship between underperformance and innovation for both historical aspirations (HA) and social aspirations (SA).

In contrast, the Threat-Rigidity perspective suggests that underperformance may also be interpreted as a severe threat—particularly when the performance gap is large—leading to narrowed search, defensive behavior, and reduced innovation. This reasoning supports H1b, predicting a negative relationship.

Integrating these perspectives, a nonlinear relationship is plausible: mild underperformance may increase innovation due to managerial confidence in overcoming the gap, while severe underperformance may reduce innovation as survival concerns dominate. This dual mechanism underlies H1c, which predicts an inverted U-shaped relationship.

H1a: Underperformance triggers problemistic search, thereby increasing innovation in response to both HA and SA.

H1b: Underperformance is perceived as a threat, leading to reduced innovation in response to both HA and SA.

H1c: The effect of underperformance is nonlinear (inverted U-shape):

Mild underperformance → innovation increases due to managerial confidence and active search.

Severe underperformance → innovation decreases as survival concerns dominate.

The pattern of this nonlinear effect may vary across firms with different capabilities.

H2: Firms respond differently depending on the type of aspiration.

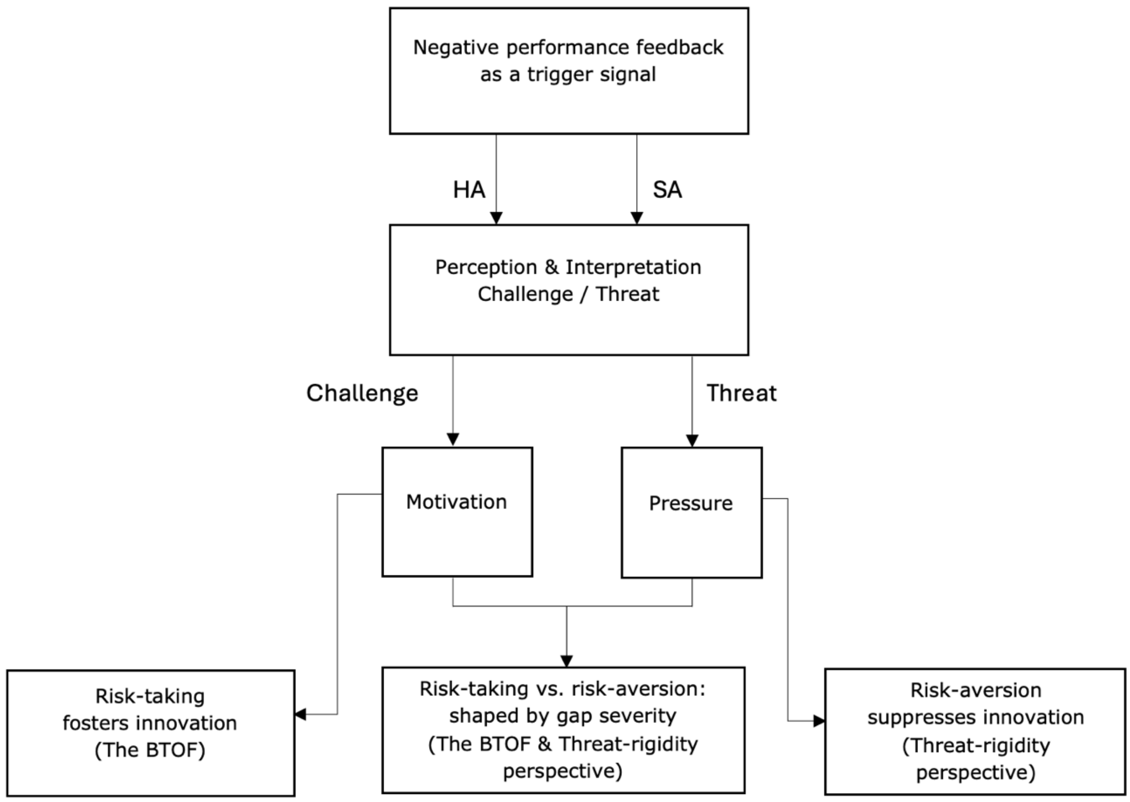
The type of aspiration may shape the salience of the performance signal and, in turn, the firm's behavioral sensitivity. HA reflects an internal benchmark that is more familiar and adjustable, which may lead to weaker or more context-dependent reactions. This reasoning supports H2a, predicting stronger reactions to HA in contexts with lower competitive pressure or when managers perceive their firm as distinct from competitors.

By contrast, SA is tied to external visibility and reputational standing, making it harder to adjust and creating stronger pressure to act. This logic underpins H2b, predicting stronger responses to SA.

H2a: Firms respond more strongly to historical aspirations (HA) in less competitive contexts or when they perceive their firm as distinct.

H2b: Firms respond more strongly to social aspirations (SA) because this benchmark is tied to reputational and competitive pressures and is harder to adjust.

Figure 1. Conceptual Framework



CHAPTER 3: RESEARCH DESIGN

Chapter 3 Methodology

This chapter outlines the research design and methodological framework used to investigate the influences of underperformance on innovation activities. Drawing on the hypotheses developed in Chapter 2, the chapter explains how the study translates theoretical constructs into empirical measures and specifies the econometric models applied in the analysis. The chapter first introduces the research's theoretical foundation, followed by a detailed description of the dataset and variable construction. It then presents the descriptive statistics, model specifications, and diagnostic procedures that ensure data suitability and methodological rigor. Finally, it discusses the estimation strategy and robustness checks implemented to validate the findings. Together, these elements establish a solid empirical basis for the results presented in Chapter 4.

3.1 Research Design

This section introduces the research design underlying the empirical investigation of how financial underperformance relative to aspiration levels influences firm innovation. The study adopts a quantitative longitudinal panel data approach, which allows for capturing dynamic relationships over time while leveraging both cross-sectional and temporal variation. The analysis covers 2014–2019, characterized by moderate yet sustained economic growth, with GDP expanding approximately 6.6% over the decade and unemployment declining from 7.0% to 4.6% (European Commission, 2021; KBC Economic Research, 2021). This macroeconomic environment is directly linked to the study's research objectives because it creates conditions where opportunity and pressure to innovate coexist. On one hand, an innovation-driven economy and increased investment encourage resources and foster opportunity-driven innovation. On the other hand, intensified competitive dynamics impose strategic pressures on firms, making performance feedback particularly salient. This dual context makes the period especially relevant for examining the research questions.

The research design is grounded in the Behavioral Theory of the Firm (Cyert & March, 1963) and extended through complementary perspectives, including the Threat-Rigidity framework (Staw, Sandelands, & Dutton, 1981). This theoretical framework not only predicts that firms' innovation responses to underperformance vary depending on the severity of performance gaps but also provides guidance on how to empirically capture such variation. Specifically, they emphasize that responses to underperformance are contingent on the reference point used to evaluate performance. This theoretical framework insight motivates the separation of two distinct aspiration measures in the empirical design: underperformance relative to historical aspiration and underperformance relative to social aspirations. By estimating the models for historical and social underperformance independently, we can prevent multicollinearity between these distinct measures, thereby enabling a clearer analysis of the differences in sensitivity to various reference points (H2).

Furthermore, the theory acknowledges that responses to underperformance may vary in form and intensity. While performance gaps can stimulate problemistic search and innovation, this reaction is not universal. In situations where resources are severely constrained or survival pressure is high, firms may instead display strategic rigidity, reducing their willingness or ability to pursue innovation (Todeva, 2007). This expectation justifies the incorporation of quadratic terms for underperformance in the econometric models, allowing for a more nuanced analysis. To evaluate this relationship empirically, the study employs pooled ordinary least squares (OLS) regressions. Pooled OLS is chosen for its ability to estimate both linear and nonlinear effects, allowing for comparisons between historical and social aspirations. Although other estimators, such as fixed-effects or random-effects models, exist, pooled OLS best aligns with the study's objective of exploring aggregate relationships rather than focusing solely on variations within and between firms.

Additionally, the decision to incorporate lagged underperformance variables is theoretically grounded. According to the BTOF, firms do not react instantaneously to performance feedback; rather, they require time to interpret signals, internal negotiation, mobilize resources, and implement innovation strategies. The use of a two-year lag operationalizes this delayed adjustment process, ensuring that the empirical specification reflects the temporal nature of behavioral responses to performance gaps.

By integrating these theoretical considerations into variable construction, model specification, and hypothesis development, the research design operationalizes abstract theoretical mechanisms into measurable empirical constructs. This ensures that the econometric models not only test statistical relationships but also meaningfully reflect the behavioral processes proposed by the theoretical framework.

While pooled OLS effectively addresses the research questions, it inherently does not fully control for unobserved firm-specific heterogeneity and potential endogeneity concerns. These limitations are mitigated through the careful use of lagged variables, including extensive controls, application of cluster-robust standard errors, and additional robustness checks, as detailed in subsequent sections. The thesis's Limitations section presents a comprehensive discussion of methodological constraints.

3.2 Data collection

3.2.1 Data source

This study utilizes a firm-level panel data set on Flemish firms, which was made available by the research supervisor specifically for this research project. The dataset combines accounting and financial data from Orbis and data on patents and trademarks from a study conducted by KU Leuven (Callaert et al., 2021). The dataset provides a rich empirical foundation for investigating the relationship between performance feedback and innovation. In particular, it offers variables relevant to this study, including financial performance indicators such as return on assets (ROA), net profit, total assets, current ratio, and firm size (measured by the number of employees), as well as innovation outputs in the form of patent and trademark counts. The longitudinal and multi-dimensional nature of the dataset makes it especially well-suited to capturing intertemporal dynamics in firm behavior, a key requirement for assessing the impact of financial underperformance on subsequent innovation output.

3.2.2 Data preparation

A systematic and structured data preparation process was employed to ensure methodological rigor and alignment with the theoretical framework. The initial dataset comprised 143,310 firm-year observations. Specific methodological and theoretical justifications guided each refinement step to validate the final analytical sample.

Initially, observations containing missing values in key variables—such as year, return on assets (ROA), patents, trademarks, total assets, and current ratio—were excluded. Subsequently, duplicate entries for the same firm-year were addressed by averaging their values. This approach preserved critical information while eliminating redundancy. Any remaining duplicates were removed to ensure that each firm-year combination uniquely represented a single observation, mitigating the risk of overweighting particular firms.

Furthermore, only firms with uninterrupted reporting over the entire period were retained to maintain temporal continuity and facilitate accurate calculations of lagged aspiration measures. This strategy resulted in a balanced panel, enhancing the interpretability of time-lagged relationships and the dynamics of aspiration gaps.

In addition, industries with fewer than five firms at the NACE 2-digit level were excluded to avoid unreliable peer benchmarks when calculating social aspirations. Although this exclusion may reduce coverage of smaller or niche industries, it ultimately enhances internal validity by ensuring that aspiration benchmarks are representative and stable.

Moreover, extreme ROA values were winsorized at the 1st and 99th percentiles. Since ROA is central to constructing historical and social aspiration gaps, failure to winsorize could distort these measures. This methodology stabilizes the data distribution, minimizes the undue influence of extreme cases, and retains the majority of the data variation. Unlike listwise deletion, winsorization preserves the panel structure and supports efficient regression estimation (Gujarati & Porter, 2009; Wooldridge, 2012).

Finally, data from 2010 to 2013 were removed after constructing the underperformance intensity variable with a two-year lag. These early years lacked the necessary historical data for proper lag calculations, which could lead to incomplete variables and model misspecification.

After applying these refinements, the final dataset consists of 59,706 firm-year observations, representing 9,951 unique firms across 70 NACE two-digit industries. A detailed breakdown of each refinement step is provided in Table 1.

Table 1. Data preparation summary

Step	Firm-Year Observations
Initial dataset (raw data)	143,310
After removing observations with missing key variables	142,780
After treating and removing duplicate firm-year entries	142,606
After retaining firms with uninterrupted data	105,330
After excluding industries with fewer than five firms	99,510
After dropping the first four years to construct lagged variables	59,706
Final dataset for analysis	59,706

3.2.3 Panel structure

The final dataset constitutes a balanced panel, covering firm-year observations from 2014 to 2019. Firms were included only if they had uninterrupted data for six years. This restriction ensures that each firm appears exactly once per year across all included years, enabling consistent construction of lagged variables and supporting longitudinal analysis of firm behavior.

Firms are classified across various economic sectors using the NACE Rev.2 two-digit industry classification system. Industries with more than five firms were retained to improve the stability and reliability of peer-based social aspiration benchmarks.

Although the dataset covers the entire Flemish economy, micro-enterprises—firms with fewer than ten employees—were excluded. These tiny firms often exhibit atypical financial dynamics and limited formal innovation activity, making them less comparable to the broader firm population under study. The final sample thus focuses on small, medium, and large firms with sufficient scale and consistency to meaningfully engage in innovation and respond to performance feedback.

This balanced panel structure supports the empirical strategy of the study by enabling the estimation of lagged effects, clean identification of aspiration gaps, and robust control for industry and year fixed effects.

3.3 Variable construction

3.3.1 Dependent variable: Innovation output

Innovation can be assessed using input and output indicators, which capture complementary dimensions of firms' innovative activities. Input indicators—such as R&D spending or innovation-related labor—reflect the effort and resources that firms devote to innovation processes. In contrast, output indicators measure the realized and market-validated results of these innovation efforts, such as patents and trademarks (Kempt et al., 2003). Therefore, output measures capture a firm's motivation to innovate and its capability to successfully transform that motivation into concrete outcomes (Dodgson, 2014). Moreover, innovation outputs are tangible, comparable across firms, and less susceptible to accounting manipulations or differences in firms' internal cost structures.

In this study, innovation output is selected as the primary indicator because the research seeks to determine whether financial underperformance leads to observable changes in innovation output, rather than merely increased innovation effort. This choice is consistent with the BTOF, which emphasizes problemistic search as a process that matters to get results in concrete strategic outcomes. Moreover, firms' responses to performance feedback depend not only on their motivation to innovate but also on their ability to convert that motivation into effective innovation results (Todeva, 2007; Ref et al., 2024) —a dimension more accurately captured by output indicators. From an empirical perspective, output data such as patent and trademark counts are standardized and comparable across firms and industries, enhancing the robustness of the analyses and supporting valid conclusions.

Patents represent technological innovations, indicating firms' capabilities in product or process advancements (Griliches, 1990; Flikkema et al., 2015). They offer abundant and stable publicly available data, enabling reliable tracking and comparability across firms and periods. However, patents have limitations: they may reflect strategic behaviors to mislead competitors, are often sector-biased toward high-tech industries, and fail to capture service-based or non-technological innovations, usually missing innovations by smaller firms due to high transaction costs (Carnabuci & Kovács, 2024). Trademarks, conversely, capture market-oriented innovations like branding, marketing, and service differentiation (Block et al., 2024; Milot, 2012). Trademarks complement patents by identifying innovations overlooked by patent data, especially in low-tech sectors and SMEs, thus significantly improving the comprehensiveness of innovation measurement (Morales et al., 2024). Combining patents and trademarks in a composite measure, therefore, leverages their strengths while mitigating individual limitations. This dual measure comprehensively captures the diverse technological and market-oriented pathways through which firms respond to underperformance. Moreover, integrating both innovation dimensions addresses methodological gaps highlighted in recent literature, enhancing the validity and generalizability of empirical findings (Kemp et al., 2003; Zhang, 2024)

The composite measure, calculated as Log(1 + Patents + Trademarks), effectively handles prevalent zero observations (95% of firm-year observations report no patents or trademarks) and skewness (7.23, as detailed in Section 3.4.2), preserving substantial variation in innovation output while facilitating robust statistical analysis (Wooldridge, 2012; Guo & Ding, 2017).

3.3.2 Independent Variables: Underperformance Intensity (UIH and UIS)

Firm performance is frequently evaluated through the return on assets (ROA) metric, a ratio defined as net income divided by total assets. This measure is a critical indicator of a firm's efficiency in utilizing its resources to generate profit. ROA is extensively employed in academic research exploring organizational learning and adaptive behavior (Bromiley, 1991; Audia & Greve, 2006). To elucidate the phenomenon of underperformance, this study constructs two key explanatory variables informed by the BTOF.

The first variable, underperformance relative to historical aspirations (UIH), quantitatively assesses how a firm’s performance deviates from its historical performance benchmarks. Historical aspiration (HA) is operationalized as the average ROA during the preceding years, specifically years t-3 and t-4. The actual performance of the firm in year t-2, denoted $P_{i,t-2}$, reflects its ROA for that period. A binary indicator, $IH_{i,t-2}$, is assigned a value of one if $P_{i,t-2}$, is less than HA, and zero otherwise. Thus, UIH is computed using the following formula: $UIH_{i,t-2} = IH_{i,t-2} * |P_{i,t-2} - HA|$.

The second variable, underperformance relative to social aspirations (UIS), captures the disparity between a firm’s performance and that of its industry peers. Social aspirations (SA) are determined by calculating the average ROA of other firms within the same two-digit NACE industry for year t-2, intentionally excluding the focal firm. A binary indicator, $IS_{i,t-2}$, is designated as one if $P_{i,t-2}$, is less than SA, and zero otherwise. UIS is then calculated using the formula: $UIS_{i,t-2} = IS_{i,t-2} * |P_{i,t-2} - SA|$.

In addition, to enhance the reliability of aspiration benchmarks, we winsorize the ROA values at the 1st and 99th percentiles during the data preparation phase. This approach minimizes the impact of outliers and ensures that extreme observations do not distort aspiration levels. This consideration is crucial given the heavy-tailed distribution commonly found in firm-level financial indicators (Gujarati & Porter, 2009).

We lag both UIH and UIS by two years relative to the dependent variable. This allows us to maintain proper temporal ordering between the independent and dependent variables, strengthening our ability to interpret causal relationships. This strategy adheres to best practices in empirical strategy and econometrics (Wooldridge, 2019; Su et al., 2023).

Furthermore, the regression models incorporate a quadratic term to investigate potential nonlinear effects of underperformance on innovation, as outlined in hypothesis H1c. We specifically look at the squared terms for underperformance variables (UIH^2 and UIS^2). This enables us to identify inverted U-shaped relationships: moderate underperformance can stimulate innovation, while severe underperformance may suppress it. Including these quadratic terms is consistent with standard econometric practices for modeling curvilinear relationships (Gujarati & Porter, 2009; Haans et al., 2016), enhancing our model’s flexibility and empirical validity.

3.3.3 Control variables

Several theoretically and empirically relevant control variables are included in the analysis to isolate the relationship between underperformance and innovation. Firstly, firm size, measured as the natural logarithm of total assets, is included because larger firms typically possess greater financial and operational resources, facilitating innovation through economies of scale, better access to external finance, and the ability to manage innovation risks (Potter, 2009). Moreover, firm size influences responsiveness to performance feedback, as larger firms often have structured processes and more significant resource buffers, affecting their strategic innovation choices (Audia & Greve, 2006).

Secondly, financial slack, operationalized as the logarithm of the current ratio (current assets divided by current liabilities), represents a firm's liquidity and available internal resources. Slack resources provide firms the financial flexibility to invest in innovation, particularly when facing performance shortfalls. Conversely, limited financial slack may constrain firms' ability to respond to negative feedback, potentially inhibiting innovation behavior (Lu & Wong, 2019; Huang et al., 2021).

Furthermore, firm age, defined as the number of years since a firm's founding (calculated as the current year minus founding year plus one), is included to control for differences in organizational capabilities and innovation behavior associated with firm maturity. Older firms generally possess established routines and accumulated knowledge, potentially enhancing their innovative capacity. However, they may also exhibit organizational inertia, making them less agile in adjusting their innovation activities following negative performance feedback (Gaveti, 2012). In addition, industry fixed effects, captured through NACE Rev. 2 two-digit dummy variables, are essential to control for sector-specific heterogeneity in innovation intensity, technological regimes, and competitive pressures. Different industries exhibit distinct innovation patterns due to varying technological opportunities, market structures, and regulatory environments, influencing firms' strategic innovation responses (Huang et al., 2021; Milot, 2012). Finally, year dummies are incorporated to control for temporal shocks, including macroeconomic fluctuations, changes in regulatory policies, and broad technological advancements that uniformly affect all firms within specific years. This control ensures that observed innovation behavior is attributed primarily to firm-specific performance dynamics rather than external temporal factors.

All continuous financial variables are log-transformed to mitigate skewness and reduce the impact of extreme values, thereby stabilizing variance and enhancing the robustness of econometric estimates. Furthermore, consistent with the theoretical assumption of delayed effects and to reduce simultaneity bias, all control variables are measured at year t−2, aligning them temporally with the main independent variables. This approach adheres to best econometric practices and strengthens the internal validity of the findings (Lucas et al., 2018). All variable constructions are summarized in Table 2 below.

Table 2. Summary of variable constructions

Variable	Measurement
Innovation output (IO)	$IO_{i,t}$ = Log(1 + Patents count + Trademarks count)
Underperformance intnesity intensity	$UIH_{i,t-2} = IH_{i,t-2} * \lvert P_{i,t-2} - HA \rvert$
relative to Historical aspiration (UIH)	$IH_{i,t-2}$ = 1 if $P_{i,t-2}$-2 < HA, else 0
Underperformance intnesity intensity	$UIS_{i,t-2} = IS_{i,t-2} * \lvert P_{i,t-2}$ -- SA$\rvert$
relative to Social aspiration (UIS)	$IS_{i,t-2}$ = 1 if $P_{i,t-2}$ < SA, else 0
Historical aspiration (HA)	HA = avg(ROA_{t-3}, ROA_{t-4})
Social aspiration (SA)	SA = avg ROA of peers in industry at t-2, excl. firm i
Firm size	Log(total assets)$_{t-2}$
Firm age	$Year_{t-2}$ − Founding year +1
Financial slack	Log(current ratio)$_{t-2}$
Industry effect	Industry dummies (NACE Rev. 2)
Year effect	Year dummies (year)

3.4 Descriptive statistics and data distribution

This section presents the descriptive statistics and data distribution for all variables used in the analysis, covering their raw values and transformed forms. The distributional assessment helps identify skewness, outliers, and other characteristics that may affect estimation. In addition, the correlation matrix provides an initial view of the relationships among variables and potential multicollinearity concerns. These descriptive insights serve as a foundation for the estimation strategy outlined in the following section.

3.4.1 Descriptive statistics

Tables 3a and 3b report the descriptive statistics and distributional properties of all variables used in the analysis. Both raw values and their natural logarithms (ln) are presented to provide a comprehensive data view. Raw values convey the actual economic scale, while log transformations normalize skewed distributions and allow proportional effects to be analyzed in the regression models.

The dataset reflects a diverse population of Flemish firms, with substantial disparities in performance, size, and innovation output. High dispersion and extreme values indicate a highly dynamic economic environment, marked by the emergence of a few market leaders. The coexistence of long-established firms and younger entrants suggests a mature yet evolving economic base.

A first observation concerns innovation output, which in its raw form has a mean of 0.15, a standard deviation of 1.98, and ranges from 0 to 178. The skewness (g1 = 49.13) and kurtosis (g2 = 3372.03) confirm the presence of a heavy right tail, indicating that most firms report no or few patents, while a small subset contributes disproportionately to total innovation. This concentration reflects the economic reality of innovation being driven by a few market leaders. After log transformation, skewness drops to 7.23 and kurtosis to 69.20, showing a substantial improvement in distributional properties while preserving meaningful differences across firms.

For financial performance (ROA), the raw data show a mean of 0.06, a high standard deviation of 0.29, and a wide range from −47.66 to 5.3, indicating substantial variation across firms, with some achieving returns well above the mean. However, the distribution is highly negatively skewed (g_1 = −84.98) with extreme kurtosis (g_2 = 12,533.44), driven by a few firms experiencing severe losses. These extreme cases are economically significant, as they represent situations in which firms face intense pressure to reconsider their strategies, potentially triggering innovation. After winsorization and log transformation, the skewness improves to 0.42 and kurtosis to 5.98, resulting in a more stable distribution suitable for regression while retaining information about underperforming firms.

By construction, the underperformance measures (UIH and UIS) are zero when firms meet or exceed aspirations and take positive values only in cases of underperformance. In the sample, their mean values are 0.03 and 0.04, respectively, with standard deviations of approximately 0.06, indicating moderate variability across firms. Most firms meet their aspiration levels or experience only mild underperformance. Both distributions exhibit positive skewness (UIH: g_1 = 3.42; UIS: g_1 = 3.15) and high kurtosis (UIH: g_2 = 19.55; UIS: g_2 = 15.60), reflecting long right tails and the presence of extreme underperformance cases. The maximum observed value for UIH is larger than that for UIS, suggesting that performance gaps relative to historical aspirations can, in some cases, be more extreme than those relative to social aspirations.

Regarding financial slack, the raw variable has a mean of 2.19 and a high standard deviation of 6.08, ranging from 0.001 to 741.56, indicating substantial differences in liquidity across firms in the sample. The extreme right skewness (g_1 = 60.22) and kurtosis (g_2 = 5,663.83) suggest that only a few firms maintain vast reserves, while most operate with limited liquidity. After log transformation, skewness decreases to 1.93 and kurtosis to 7.69, confirming that the transformation produces a more symmetric distribution and reduces the influence of extreme values, making the variable more suitable for regression analysis.

Firm size exhibits a similar pattern, with raw values showing a mean of 40.81 million and a standard deviation of 660.62 million, ranging from 0.01 to 54,588 million, indicating substantial variability and a distribution heavily influenced by a few huge firms. The skewness (g_1 = 57.26) and kurtosis (g_2 = 3,972.55) further confirm the presence of dominant players in the industry. After log transformation, firm size has a mean of 15.28 and a standard deviation of 1.54, with skewness reduced to 0.89 and kurtosis to 4.90, resulting in a more balanced distribution that facilitates proportional comparisons in the regression models.

Finally, firm age has a mean of 28.2 years, indicating that, on average, firms in the sample have a long operational history. The standard deviation of 15.4 years and the range from 3 to 146 years reflect substantial diversity in market experience. The skewness (g_1 = 1.32) and kurtosis (g_2 = 6.34) indicate a distribution that is relatively closer to normality compared to other variables in the dataset. This diversity is economically relevant, as it captures both young and mature firms, which may differ in their innovation behaviors and responses to performance feedback.

Table 3.a. Descriptive statistics and data distribution (Pooled Panel Data)

	Mean		SD		Min		Max	
	raw	ln	raw	ln	raw	ln	raw	ln
Output	0.15	0.05	1.98	0.27	0.00	0.00	178	5.19
ROA	0.06	0.06	0.29	0.11	-47.66	-0.32	5.32	0.47
UIH	0.03	—	0.06	—	0.00	—	0.79	—
UIS	0.04	—	0.06	—	0.00	—	0.49	—
UIH2	0.004	—	0.02	—	0.00	—	0.63	—
UIS2	0.005	—	0.02	—	0.00	—	0.24	—
Age	28.23	—	15.42	—	3.00	—	146.00	—
Slack	2.19	0.98	6.08	0.47	0.001	0.001	741.56	6.61
Firm size	40.81	15.28	661.62	1.54	0.01	9.16	54,588.81	24.72

Note: Firm size is reported in millions of raw data.

Table 3.b. Descriptive statistics and data distribution (Pooled Panel Data)

	Skewness (g1)		Kurtosis (g2)	
	raw	ln	raw	ln
Output	49.13	7.23	3372.03	69.20
ROA	-84.98	0.42	12533.44	5.98
UIH	3.42	—	19.55	—
UIS	3.15	—	15.60	—
UIH^2	10.74	—	201.30	—
UIS^2	6.28	—	46.88	—
Age	1.32	—	6.34	—
Slack	60.22	1.93	5663.83	10.69
Firm size	57.26	0.89	3972.55	4.90

3.4.2 Correlation Matrix

The correlation matrix (Table 4) provides an overview of the pairwise relationships among key variables, offering a preliminary assessment of potential multicollinearity and ensuring consistency with theoretical expectations. Most correlations between independent variables and control variables fall within acceptable ranges, indicating limited concerns for multicollinearity (Hair et al., 2010).

Table 4. Correlation Matrix

	Output	UIH	UIH^2	UIS	UIS^2	Slack	Firm size	Age
Output	1.0000**							
UIH	-0.0093*	1.0000**						
UIH^2	-0.0070	0.8633**	1.0000**					
UIS	0.0027	0.5367**	0.4998**	1.0000**				
UIS^2	0.0010	0.5398**	0.5639**	0.8963**	1.0000**			
Slack	0.0028	-0.0272**	-0.0479**	-0.1938**	-0.1377**	1.0000**		
Firm size	0.2516**	-0.0983**	-0.0924**	-0.0617**	-0.0847**	0.1067**	1.0000**	
Age	0.0724**	-0.0636**	-0.0534**	-0.0228**	-0.0440**	0.1537**	0.3069**	1.0000**

***Correlation is significant at the 0.01 level, *Correlation is significant at the 0.05 level*

The dependent variable, innovation output, exhibits a statistically significant but negligible correlation with underperformance relative to historical aspiration (UIH), with a coefficient of r = -0.0093 ($p < .05$). This result, while consistent with a weak linear association as posited in Hypothesis H1b, likely reflects the effect of large sample size rather than substantive theoretical relevance. In contrast, UIH^2 does not correlate significantly with innovation output, suggesting no observable non-linear relationship in the simple correlation structure.

For underperformance relative to social aspiration (UIS), neither the linear nor the squared term displays a statistically significant correlation with innovation output, suggesting no direct association at the descriptive level. However, this absence of a bivariate relationship does not rule out the relevance of UIS in explaining innovation. In line with Hypothesis H2, the distinction correlations between UIH and UIS may become more apparent in regression models that control for firm-level characteristics and allow for different behavioral responses to alternative aspiration benchmarks.

Regarding firm-level controls, firm size (measured by total assets) is moderately and significantly correlated with innovation output ($r = 0.2516$, $p < .001$), indicating that larger firms are generally more innovative. A weaker but still statistically significant correlation is found with firm age ($r = 0.0724$, $p < .001$), suggesting that accumulated experience may support innovation, though the effect is modest.

As expected, powerful negative correlations are observed between each underperformance variable and its squared counterpart—UIH and UIH^2 ($r = 0.8633$), UIS and UIS^2 ($r = 0.8963$), both significant at the 1% level. These high correlations arise naturally due to their mathematical construction and do not violate the assumption of no perfect multicollinearity (Wooldridge, 2012). Still, their inclusion in regression models warrants further scrutiny using Generalized Variance Inflation Factors, which will be examined in Section 3.6.2.

No problematic correlations are found among the remaining independent and control variables. For instance, while UIH and UIS show a moderate positive correlation ($r = 0.5367$, $p < .001$), this is theoretically expected given that both reflect firm underperformance, albeit relative to different benchmarks. Control variables such as slack, size, and age show no multicollinearity concerns.

In summary, the correlation matrix reveals no severe collinearity issues and offers preliminary support for the relationship between firm structural attributes and innovation. However, no clear linear or curvilinear associations are observed between underperformance and innovation output at this stage, reinforcing the need for formal regression analysis with quadratic terms.

3.5 Econometric Model Specification

This study investigates how financial underperformance—measured as deviations from historical and social aspirations—affects firms' innovation output. Building on the Behavioral Theory of the Firm (Cyert & March, 1963; Greve, 2003), it tests whether underperformance leads to increased innovation (H1a), reduced innovation (H1b), or follows a nonlinear, inverted U-shaped pattern where moderate gaps encourage innovation but severe gaps suppress it (H1c). Hypotheses H2a and H2b examine whether firms respond differently to historical versus social aspiration gaps.

The estimation method is chosen with attention to theoretical fit and empirical reliability. Pooled OLS is applied because it uses variation across and within firms, making it efficient for panels with many firms but few periods. This method is supported by Wooldridge (2010). It aligns with Haans et al. (2016), who provide guidelines for testing U-shaped relationships, suggesting that pooled OLS, when correctly specified, is capable of detecting nonlinear patterns. Unlike fixed-effects models, which remove cross-sectional differences, pooled OLS retains this variation, which is theoretically vital for understanding heterogeneous innovation responses. To mitigate its limitations, the model integrates lagged predictors, industry and year fixed effects, and key controls to reduce omitted variable bias.

The inclusion of quadratic terms is a deliberate modeling choice. Theory and empirical evidence suggest that the magnitude of underperformance influences innovation in a non-monotonic way. Moderate shortfalls stimulate search and experimentation (Liu et al., 2024), while severe underperformance can limit resources and suppress innovation (Chen & Miller, 2007). Haans et al. (2016) confirm that quadratic specifications allow researchers to detect these dynamics, avoiding the constraints of a pure linear assumption. Therefore, to explore the nature of the relationship shape, we conduct both linear and nonlinear model specifications.

The two-year lag structure for underperformance and controls reflects how feedback processes unfold in practice. Firms need time to interpret underperformance signals, adjust strategies, and generate innovation output. This lag is supported by Cyert and March (1963) and econometric literature (Gujarati & Porter, 2009; Wooldridge, 2019), which emphasizes temporal ordering to improve causal interpretation. Empirical work, such as9. (2018), similarly uses lagged measures to capture delayed effects.

Separate models for UIH and UIS are estimated to ensure conceptual clarity. UIH reflects self-referential learning, while UIS captures competitive benchmarking. Including both in a single model risks multicollinearity and makes interpretation difficult. Prior studies (Lucas et al., 2018) also analyze these benchmarks separately to isolate their distinct effects.

Accordingly, the general regression equation is as follows:

Linear specification model

$Y_{i,t} = \beta 0 + \beta 1 * X_{i,t-2} + \beta x * Controls_{i,t-2} + \varepsilon_{I,t-2}$

Nonlinear specification model

$Y_{i,t} = \beta 0 + \beta 1 * X_{i,t-2} + \beta 2 * X_{i,t-2} + \beta x * Controls_{i,t-2} + \varepsilon_{I,t-2}$

$Y_{i,t}$ = Dependent variable at time t

$\beta 0$ = intercept

$X_{i,t-2}$ = independent variable at time t-2

βk = coefficient parameter

$Control_{i,t-2}$ = control variables at t-2

ε = error term

Four models are specified in Table 5 below

Table 5. Regression models

Model	Dependent variables	Equation
Linear	Underperformance related to Socaial aspiration (UIH)	$IO_{i,t}$ = β0+ β1∗$UIH_{i,t-2}$+ βx*$Controls_{i,t-2}$ +$\varepsilon_{I,t-2}$
Nonlinear	Underperformance related to Socaial aspiration (UIH)	$IO_{i,t}$ = β0+ β1∗$UIH_{i,t-2}$+ β2∗$UIS_{i,t-2}$+ βx*$Controls_{i,t-2}$ +$\varepsilon_{I,t-2}$
Linear	Underperformance related to Social aspiration (UIS)	$IO_{i,t}$ = β0+ β1∗$UIS_{i,t-2}$+ βx*Controlsi,t-2+$\varepsilon_{I,t-2}$
Nonlinear	Underperformance related to Social aspiration (UIS)	$IO_{i,t}$ = β0+ β1∗$UIS_{i,t-2}$+ β2∗$UIS_{i,t-2}$+ βx*$Controls_{i,t-2}$+$\varepsilon_{I,t-2}$

The four baseline models are estimated using pooled OLS with cluster-robust standard errors (CR2 correction). This approach is adopted because it corrects for heteroskedasticity and within-firm autocorrelation, thereby ensuring reliable inference despite the violations of classical OLS assumptions identified in Section 3.6. Moreover, the CR2 correction, recommended by Cameron and Miller (2015), is particularly appropriate for panel data characterized by a large number of firms (N) and a short time dimension (T).

With this estimation strategy, the coefficients can be interpreted directly in relation to the hypotheses, basically. Specifically, in both the linear and nonlinear specification models, a positive and significant coefficient on the linear term (β1) supports H1a, whereas a negative and significant β1 supports H1b. For the nonlinear specification, the signs and significance of both β1 (linear term) and β2 (quadratic term) determine whether the relationship is nonlinear. A negative β2 with an opposite sign to β1 indicates an inverted U-shaped relationship, supporting H1c. Conversely, a positive β2 with an opposite sign to β1 reflects a U-shaped relationship, providing only partial support for the nonlinear aspect of H1c. Interpretation considers not only the sign but also the magnitude and statistical significance of these coefficients.

Furthermore, differences in the estimated coefficients between the UIH and UIS models provide evidence for H2a and H2b, as they reveal whether firms react more strongly to historical or social aspiration gaps.

Nevertheless, pooled OLS has limitations, particularly in controlling for unobserved firm-specific heterogeneity and potential endogeneity. These limitations are acknowledged and partially addressed by using a two-period lag structure, including fixed effects in alternative specifications, and conducting robustness checks.

3.6 Diagnostic Tests

To ensure the robustness and reliability of the econometric models, a series of diagnostic tests was conducted. These include assessments of multicollinearity, autocorrelation, heteroskedasticity, and normality. The results of these tests guided model adjustments and validated the suitability of the chosen estimation methods. The assessment is conducted separately for four regression models. Two models: linear and nonlinear specifications using underperformance relative to historical aspiration (Model 1 & Model 2, respectively). Similarly, the two others use underperformance relative to social aspiration as key predictors of innovation output (Model 3 for linear & Model 4 for nonlinear).

3.6.1 Multicollinearity

OLS regression assumes that explanatory and control variables are not perfectly correlated with one another. Violations of this assumption give rise to multicollinearity, which inflates standard errors and reduces the reliability of coefficient estimates (Wooldridge, 2012; Gujarati & Porter, 2009). Although multicollinearity does not bias OLS coefficients, it undermines their precision and may obscure the individual contribution of predictors, thereby weakening statistical inference.

Preliminary evidence from the correlation matrix revealed strong associations between each underperformance measure and its squared term. However, such bivariate relationships are insufficient to assess multicollinearity in a multivariate regression context, especially when control variables and fixed effects are included. To evaluate the extent of linear dependence more formally, this study computes Generalized Variance Inflation Factors (GVIFs) for all explanatory and control variables (Fox & Monette, 1992).

For regression with predictors with multiple degrees of freedom—such as industry dummies—GVIF values were adjusted using the transformation GVIF^(1/(2*Df), which allows direct comparability with conventional VIF thresholds (Fox, 2015). This adjustment is widely adopted in applied research involving categorical variables (e.g., Sheather, 2009; Tay, 2017), with values exceeding $\sqrt{10} \approx 3.16$ commonly interpreted as indicating severe multicollinearity (Belsley et al., 1980).

The results of the multicollinearity diagnostic using generalized variance inflation factors (GVIF) for all models are presented in Table 6(a,b,c,d)

Table 6a. GVIF Statistics for Model 1 – UIH Linear specification

	GVIF	Df	GVIF^(1/(2*Df)
UIH	1.03	1	1.01
Age	1.23	1	1.11
Total Assets	1.40	1	1.18
Slack	1.08	1	1.04
Factor(Dummy year)	1.02	5	1.00
Factor(Dummy industry)	1.49	70	1.00

Table 6b. GVIF Statistics for Model 2 – UIH Nonlinear Specification

	GVIF	Df	GVIF^(1/(2*Df)
UIH	3.96	1	1.99
UIH^2	3.95	1	1.99
Age	1.23	1	1.11
Total Assets	1.40	1	1.18
Slack	1.09	1	1.04
Factor(Dummy year)	1.02	5	1.00
Factor(Dummy industry)	1.49	70	1.00

Table 6c. GVIF Statistics for Model 3 – UIS Linear Specification

	GVIF	Df	GVIF^(1/(2*Df)
UIS	1.06	1	1.03
Age	1.23	1	1.11
Total Assets	1.40	1	1.18
Slack	1.13	1	1.06
Factor(Dummy year)	1.01	5	1.00
Factor(Dummy industry)	1.50	70	1.00

Table 6d. GVIF Statistics for Model 4 – UIS Nonlinear Specification

	GVIF	Df	GVIF^(1/(2*Df)
UIS	5.31	1	2.30
UIS^2	5.22	1	2.28
Age	1.23	1	1.11
Total Assets	1.40	1	1.18
Slack	1.14	1	1.07
Factor(Dummy year)	1.02	5	1.00
Factor(Dummy industry)	1.51	70	1.00

*Note: GVIF^(1/(2*Df) > 3.16 is signal of multicollinearty*

Following the guidelines of Fox and Monette (1992) and Belsley et al. (1980), GVIF^(1/(2*Df) values exceeding 3.16 indicate potential multicollinearity. For the UIH model in the linear specification (Table 6a), the value for UIH (1.01) is well below this threshold, and all control variables—including industry and year dummies—show acceptable correlation levels. In Model 2 (Table 6b), the values for UIH (1.99) and its squared term, $UIH2^2$ (1.99), also remain comfortably below the cutoff, indicating that the quadratic specification does not introduce problematic multicollinearity.

Similarly, in the UIS models, the value for UIS in Model 3 (1.03; Table 6c) and the values for UIS (2.30) and UIS22 (2.28) in Model 4 (Table 6d) are slightly higher than those for UIH but still below the 3.16 threshold, suggesting acceptable correlation between the linear and quadratic terms. For both sets of models, control variables (Age, Total Assets, Slack) and the year and industry dummies consistently yield values close to 1.00, confirming negligible multicollinearity for these variables.

These results align with the earlier correlation matrix, which showed low pairwise correlations among all explanatory variables, except for the expected high correlation between each underperformance measure and its squared term. This correlation is inherent to polynomial specifications and does not compromise estimation. Overall, the GVIF diagnostics indicate that multicollinearity is not a concern in any of the models, and the inclusion of quadratic terms does not undermine the stability or interpretability of the regression estimates.

3.6.2 Autocorrelation

The pooled OLS models in this study use both between-firm and within-firm variation while controlling for observable heterogeneity. For these models to provide valid inference, the error terms must not be serially correlated within firms. When this assumption is violated, standard errors tend to be underestimated, which can lead to overstated statistical significance. This issue is particularly critical in short panel datasets (Wooldridge, 2010; Potter & Guart, 2009).

To verify this assumption, the study applies the regression-based test for first-order serial correlation proposed by Wooldridge (2010). This method is specifically designed for pooled panel data. It involves re-estimating the pooled OLS model after adding the lagged residuals from the original regression as an additional explanatory variable. If the coefficient on the lagged residual is not significantly different from zero, the null hypothesis of no serial correlation is not rejected. A significant coefficient, in contrast, indicates the presence of serial correlation. This test is appropriate for the present analysis because it accommodates the panel structure of the data, produces valid results under heteroskedasticity, and provides a reliable way to check whether serial correlation may distort the pooled OLS estimates.

The test was conducted separately for all models, and because the results were nearly identical, they are reported jointly. In all four models, the estimated coefficient on the lagged residual is approximately 1353.19, and p-values$< .001$. These results decisively reject the null hypothesis, providing strong evidence that the residuals are serially correlated within firms, thereby violating the classical OLS independence assumption.

The detection of autocorrelation justifies the use of cluster-robust standard errors, a correction explicitly recommended by Wooldridge (2010) for econometric analyses of panel data with such characteristics. This adjustment (CR2) effectively accounts for arbitrary forms of within-firm serial correlation and heteroskedasticity, ensuring that inference on coefficient estimates remains valid. With this adjustment in place, the analysis proceeds to examine the assumption of homoskedasticity of the error variance, as discussed in Section 3.6.3.

3.6.3 Heteroskedasticity

Building on the results of Section 3.6.2, which confirmed the presence of serial correlation in the residuals, the evaluation of heteroskedasticity further tests the validity of the pooled OLS estimation. In panel data contexts, heteroskedasticity—where the error variance systematically varies across observations—can distort standard error estimates and compromise inference. This issue is particularly critical for pooled OLS, where intra-firm dependence complicates the direct application of conventional cross-sectional tests (Wooldridge, 2010).

To address this, the study employs an adjusted Breusch–Pagan Lagrange Multiplier (LM) test developed by Wooldridge (2010), which explicitly accounts for the panel structure. Unlike standard Breusch–Pagan or White tests, this version regresses squared residuals on the original regressors while preserving temporal clustering, making it suitable for short panels. Since the results for all four models are identical, we will report them together. The results provide strong evidence of heteroskedasticity: the LM statistic is around 13.18 ($df = 80$, $p < .001$), leading to rejection of the null hypothesis of constant variance. However, because this test assumes residual independence, which was shown to be violated in Section 3.6.2, the magnitude and significance of the LM statistics may be weakened.

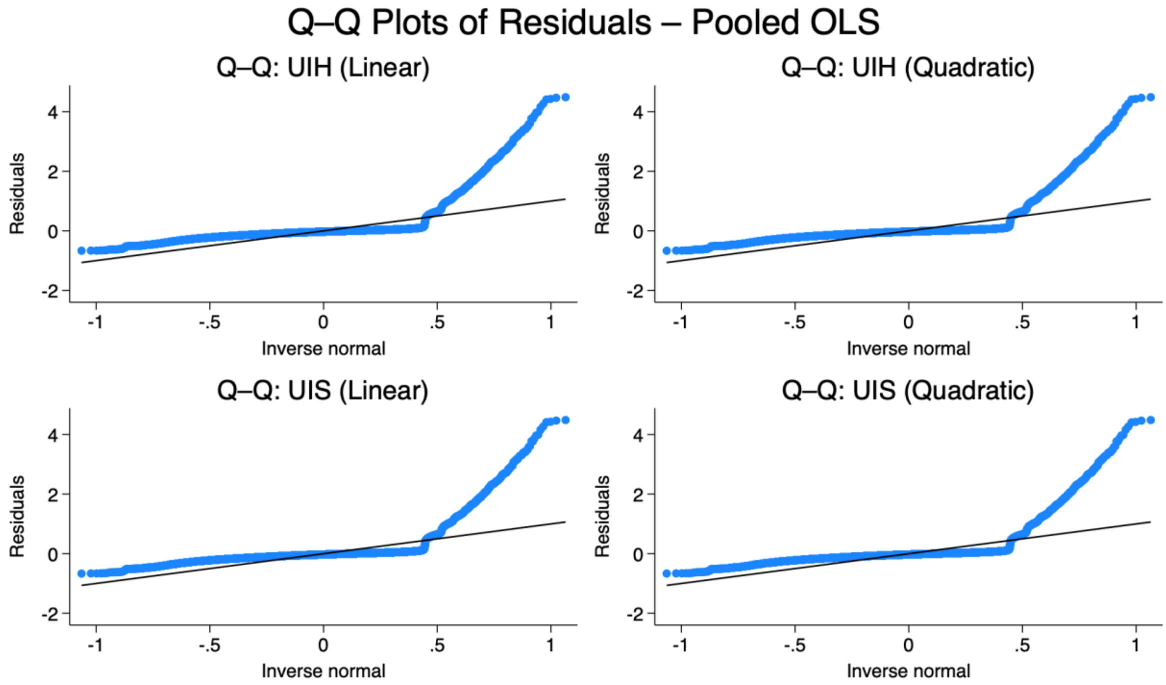
Overall, these results confirm the violation of the homoskedasticity assumption and, together with the evidence of serial correlation, justify the use of cluster-robust standard errors. This estimation approach, recommended by Wooldridge (2010), corrects for both heteroskedasticity and within-firm error dependence, thereby ensuring valid inference in the pooled OLS models.

3.6.4 Normality of Residuals

Following the detection of heteroskedasticity and serial correlation in Sections 3.6.2 and 3.6.3, the residuals from the pooled OLS models were further examined for normality. Although residual normality is not a requirement for the consistency or unbiasedness of OLS estimators, it can influence the reliability of conventional t- and F-tests in small samples under homoskedastic conditions. In this study, the panel is characterized by a large number of firms ($N \approx 9{,}951$) and a short time dimension ($T = 6$), which implies that the asymptotic properties of the estimators—supported by the Central Limit Theorem—hold regardless of the residual distribution. Moreover, inference does not depend on normality because cluster-robust standard errors are employed, which remain valid under both heteroskedasticity and non-normality (Wooldridge, 2010). Despite this, residual normality checks provide a more complete understanding of the error structure. Both formal testing and graphical analysis were applied.

The Jarque–Bera (JB) test decisively rejects normality across specifications—Linear UIH: JB = 7,842,926, $p < .001$; Linear UIS: JB = 7,845,280, $p < .001$; Nonlinear (Quadratic) UIH: JB = 7,842,594, $p < .001$; Nonlinear (Quadratic) UIS: JB = 7,839,756, $p < .001$. Meanwhile, graphical diagnostics corroborate these findings. Figure 2 presents normal Q–Q plots of residuals from the four pooled OLS models (UIH linear, UIH quadratic, UIS linear, UIS quadratic). The x-axis (Inverse normal) shows theoretical normal quantiles, and the y-axis (Residuals) shows ordered sample residuals: points close to the 45° reference line indicate approximate normality, whereas systematic departures reflect non-normality due to skewness/kurtosis or outliers. In our plots, points rise sharply in the upper tail across all four panels, while mid-quantiles track the line reasonably well—evidence of positive skewness and excess kurtosis. Patterns are very similar for UIH and UIS, and adding a quadratic term does not alter the shape, suggesting the deviations are not due to a missing simple quadratic nonlinearity. Because normality is not required for OLS consistency, inference relies on heteroskedasticity-robust standard errors (and cluster-robust by firm where serial correlation is detected). Given the large sample and our robust estimation strategy—particularly the use of cluster-robust standard errors—these departures from normality do not compromise the validity of statistical inference but underscore the importance of the robust approach adopted.

Figure 2 Q-Q plot of Residuals



Note: Q–Q plots compare sample residual quantiles with theoretical normal quantiles. Upward departures in the upper tail across all four specifications indicate right-skewness and excess kurtosis; thus, residuals are non-normal.

3.7 Estimation Strategy and Model Assessment

This section synthesizes and evaluates the research design developed across Sections 3.1 to 3.6, articulating the estimation strategy employed to analyze the econometric models specified in Section 3.5 and assessing the robustness of the entire design to ensure reliable answers to the research questions. This evaluation demonstrates why each component is necessary, how potential issues are mitigated, and why the findings to be reported in Chapter 4 are trustworthy, aligning with established methodological standards.

3.7.1 Estimation Strategy

The estimation strategy follows the econometric specifications in Section 3.5 and estimates pooled OLS models to recover precise and reliable relationships between financial underperformance and innovation output. All work was carried out in Stata—including data preparation (panel setup and lag construction), descriptive statistics, correlation matrices, all regressions, specification tests (heteroskedasticity and serial correlation), and figures. Only one diagnostic used R: generalized variance inflation factors (GVIFs), computed with the car package's vif() function, which allows grouping related regressors (e.g., a variable with its squared term or factor dummies) and reports the adjusted measure GVIF^(1/(2*Df) as in Fox and Monette (1992). Stata's built-in vif provides variable-by-variable VIFs and does not implement grouped GVIFs or this adjusted scaling, which motivated the one-off use of R.

To ensure valid inference, cluster-robust standard errors with CR2 correction are applied. This technique adjusts the variance estimates to remain valid when error terms are heteroskedastic or correlated within clusters (firms). By doing so, it prevents underestimated standard errors, reduces the risk of overstating statistical significance, and enhances the credibility of the estimated coefficients in the estimation strategy.

To determine the shape posited in H1, the analysis proceeds in two stages. We first estimate a linear specification to assess whether underperformance is monotonically related to innovation output; if the coefficient on underperformance is statistically and economically significant, its sign indicates a positive (H1a) or negative (H1b) association. We then estimate a quadratic specification to allow curvature. If the squared term is not significant, we retain the linear interpretation and base inference on the linear coefficient. If the squared term is significant, we treat the relationship as nonlinear and evaluate its shape.

Following Lind and Mehlum (2010), guided by Haans et al. (2016), an inverted-U is concluded only if all three conditions hold: (i) curvature: the quadratic coefficient is negative ($\beta 2<0$); (ii) end-point slopes: the slope at low underperformance is significantly positive while the slope at high underperformance is significantly negative (i.e., opposite signs at the lower and upper bounds of the observed range); and (iii) turning point: the estimated maximum lies within the observed range of underperformance and its confidence interval is also inside that range. (The symmetric logic applies for a U-shape when $\beta 2>0$)

We then compare the linear and quadratic models on (a) the magnitudes and p-values of $\beta 1$ (and $\beta 2$ where applicable) and (b) overall fit and incremental improvement—using R-square. Conclusions are drawn only after this sequence: if the quadratic term adds no meaningful improvement, we retain the linear form for parsimony; if it does and the Lind–Mehlum conditions are met, we conclude an inverted-U; otherwise, we characterize the detected monotonic or U-shaped pattern accordingly.

After testing H1, Hypothesis H2 is evaluated by comparing the coefficients of the two models (UIH and UIS). The comparison considers both the magnitude and p-values of the coefficients, with 95% confidence intervals serving as an additional benchmark. These intervals not only indicate the range within which the true parameter is likely to fall but also allow a visual and statistical check of whether estimates from different models overlap. When intervals do not overlap, it provides clear statistical evidence that the coefficients are likely to be significantly different, strengthening conclusions about differences between models. Standard errors (SE) remain crucial for assessing how precisely each coefficient is estimated and for comparing whether differences between coefficients are meaningful. Meanwhile, F-tests provide further evidence on overall model significance and the joint validity of the estimated parameters.

To reinforce the findings, several robustness checks are conducted. First, Wald tests are applied to assess the joint significance of the linear and quadratic terms in each model, thereby strengthening the interpretation of these coefficients. Second, alternative lag structures—such as a three-period lag ($t-3$)—are estimated to examine the temporal stability of the results. Third, zero-inflated negative binomial models are employed to account for the potential influence of excess zero observations on the main results. Fourth, fixed-effects specifications are estimated to control for unobserved, time-invariant firm heterogeneity. Finally, subsample analyses compare the responses of SMEs with those of larger firms to identify whether meaningful differences exist between these groups.

All robustness checks are implemented in Stata using the same cluster-robust methodology to ensure consistency with the primary estimation framework.

3.7.2 Model Assessment

The research design and estimation strategy are rigorously crafted to ensure robust, valid findings capable of addressing the research questions and testing the hypotheses. The theoretical framework (Section 3.1), grounded in the Behavioral Theory of the Firm (Cyert & March, 1963; Greve, 2003), provides a strong conceptual basis by aligning the hypotheses with established literature, ensuring theoretical soundness and relevance. The dataset (Section 3.2), comprising 59,706 observations across 9,951 firms from 2014 to 2019, offers a large, representative sample that enhances statistical power, mitigates sampling bias, and ensures generalizability (Cameron & Miller, 2015). The variable measurements (Section 3.3) minimize measurement error by clearly defining underperformance relative to historical (UIH) and social (UIS) aspirations, while including appropriate controls (slack, firm size, age, dummies industry, and dummies year) to limit confounding effects.

Descriptive statistics (Section 3.4) validate data quality by confirming substantial variation in firm size, age, and performance, ensuring that the sample captures a diverse range of firm contexts. The model specifications (Section 3.5) employ pooled OLS with separately linear and quadratic terms and industry/year fixed effects to test hypothesized linear and nonlinear relationships, aligning with the study's cross-sectional focus and theoretical foundation. Diagnostic tests (Section 3.6) indicate the absence of multicollinearity, but reveal the presence of heteroskedasticity, autocorrelation, and non-normality of residuals. The latter is not considered problematic given the large sample size, which ensures asymptotic normality of the estimators. Heteroskedasticity and autocorrelation are addressed through the use of cluster-robust standard errors, ensuring valid statistical inference.

The estimation strategy (Section 3.7.1) builds on this foundation. Pooled OLS is implemented in Stata, with cluster-robust standard errors (CR2) to address heteroskedasticity and within-cluster autocorrelation (Cameron & Miller, 2015). This ensures reliable inference by preventing underestimated standard errors and overstated significance. Hypothesis H1 is tested by examining the coefficients $\beta 1$ (linear and nonlinear model) and $\beta 2$ (nonlinear model); the significance of the quadratic term triggers the Lind and Mehlum (2010) procedure, verifying an inverted U-shape through conditions on the sign of linear and quadratic coefficient, slope at data extremes, and the location of the turning point (Haans et al., 2016). Hypothesis H2 is evaluated by comparing $\beta 1$and $\beta 2$ between UIH and UIS models, using magnitude, p-values, 95% confidence intervals, and F-tests to determine whether firms react more strongly to one aspiration reference.

Robustness is assessed through Wald tests, alternative lag structures (e.g., $t-3$), subsample analyses (SMEs vs. larger firms), zero-inflated negative binomial models, restricted linear models, and fixed-effects specifications to control for unobserved heterogeneity, thereby confirming the consistency and reliability of the results.

Although potential issues remain—such as residual endogeneity, limited temporal coverage, and heterogeneous firm responses—these risks are systematically minimized through control variables, fixed effects, diagnostic tests, and extensive robustness checks. Each methodological choice is necessary and non-redundant, ensuring that the findings are credible and theoretically grounded.

Collectively, the integrated research design and estimation strategy adhere to econometric best practices and leverage the strengths of a large, high-quality dataset. This comprehensive approach provides strong confidence that the results reported in Chapter 4 will robustly address the research questions and contribute meaningfully to the literature on underperformance and innovation.

CHAPTER 4: RESULTS

This chapter reports the empirical findings from pooled OLS analyses conducted in Stata to test the proposed hypotheses. The results address the research questions by examining how financial underperformance relative to historical and social aspirations shapes innovation output (H1) and whether firms respond differently to these two aspiration levels (H2).

4.1 Main Regression Results

This section reports the estimation outcomes for Hypotheses H1a–H1c and H2a–H2b. Two pooled OLS models with CR2 corrections are applied, distinguishing the effects of underperformance relative to historical and social aspirations.

Impact of underperformance on innovation (Hypothesis 1)

Table 7.a presents the estimation results of the linear and non-linear regressions examining the effect of underperformance relative to historical aspirations on innovation output, based on 59,706 firm-year observations from 9,950 unique firms (clusters).

Table 7.a: Regression Results — UIH

	Linear Model				Non-linear Model			
Variables	Coefficient	Robust SE	95% CI	p-value	Coefficient	Robust SE	95% CI	p-value
UIH	0.055	0.017	[0.02, 0.09]	.001**	0.016	0.035	[-0.52, 0.08]	.642
UIH²	—	—	—	—	0.158	0.11	[-0.06, 0.37]	.151
Firm size	0.046	<0.01	[0.04, 0.05]	.001**	0.046	<0.01	[0.04, 0.05]	.000**
Slack	-0.017	<0,01	[-0.03, -0.01]	.000**	-0.017	<0.01	[-0.03, -0.01]	.001**
Age	0.000	<0.01	[-0.00, 0.00]	.949	0.000	<0.01	[-0.00, -0.00]	.954

	Linear Model				Non-linear Model			
Variables	Coefficient	Robust SE	95% CI	p-value	Coefficient	Robust SE	95% CI	p-value
Observations	59,706				59,706			
Clusters	9950				9950			
R^2	0.094				0.094			
F-statistic	5.87				5.79			

In the linear specification, UIH has a positive and statistically significant coefficient (β1=0.055, p=.001). This indicates that, holding other variables constant, higher underperformance relative to historical aspirations is associated with higher innovation output. The confidence interval excludes zero (95% CI [0.021, 0.089]), confirming the robustness of the effect.

Meanwhile, in the extended specification with a quadratic term, the coefficient for UIH becomes statistically insignificant (β1=0.016, p=.642), and UIH^2 is also insignificant (β2=0.158, p=.151). Hence, there is no empirical support for a non-linear relationship.

The explanatory power of both models is identical (R2=0.094), and the F-statistic is slightly higher in the linear model (5.87) than in the non-linear model (5.79). Given that the quadratic term does not improve model fit and is not statistically significant, the linear model is preferred following the parsimony principle (Burnham & Anderson, 2002; Box & Jenkins, 1976).

The results in Table 7. a indicate a positive linear relationship between UIH and innovation output as UIH increases, innovation output increases (H1a). No statistically significant evidence is found for a non-linear effect.

Table 7. b: Regression Results — UIS

	Linear Model				Non-linear Model			
Variables	Coefficient	Robust SE	95% CI	p-value	Coefficient	Robust SE	95% CI	p-value
UIS	0.032	0.023	[-0.01, 0.08]	.164	-0.106	0.057	[-0.22, 0.01]	.062
UIS^2	—	—	—	—	0.506	0.18	[0.16, 0.85]	.004*
Firm size	0.046	<0.01	[0.04, 0.05]	.000**	0.046	<0.01	[.04, 0.05]	.000**
Slack	-0.016	<0.01	[-0.03, -0.01]	.001**	-0.017	<0.01	[-0.03, -0.01]	.000**

	Linear Model				Non-linear Model			
Variables	Coefficient	Robust SE	95% CI	p-value	Coefficient	Robust SE	95% CI	p-value
Age	0.000	<0.01	[-0.00, 0.00]	.980	0.000	<0.01	[-0.00, 0.00]	.935
Observations	59,706				59,706			
Clusters	9950				9950			
R^2	0.094				0.094			
F-statistic	5.86				5.79			

Table 7.b presents the estimation results of the linear and non-linear regressions examining the effect of underperformance relative to social aspirations on innovation output, based on 59,706 firm-year observations from 9,950 unique firms (clusters), with standard errors clustered at the firm level.

In the linear specification, UIS has a positive but statistically insignificant coefficient ($\beta 1=0.032$, $p=.164$), with the 95% confidence interval ([−0.01, 0.08]) including zero. This suggests a potential positive association, but the effect is not statistically different from zero when only the linear term is considered.

In the quadratic specification, the coefficient for UIS becomes negative and marginally insignificant ($\beta 1=-0.106$, $p=.062$), while the quadratic term UIS^2 is positive and statistically significant ($\beta 2=0.506$, $p=.004$, 95% CI [0.16, 0.85]). The negative and significant coefficient for UIS and the positive and significant coefficient for UIS^2 indicate that the relationship is U-shaped. The explanatory power of both models is identical ($R^2=0.094$), and the F-statistic is slightly higher in the linear model (5.86) than in the non-linear model (5.79). However, given the statistical significance of the quadratic term, the non-linear model offers a better representation of the relationship between UIS and innovation output.

To explore the nature of the relationship, we follow the procedure of Haans, Pieters, and He (2016) to examine the turning point and slopes, as reported in Table 8. The quadratic specification results (Table 7.b) indicate that the coefficient of the linear term for UIS is negative ($\beta 1 = -0.016$) and the quadratic term is positive and statistically significant ($\beta 2 = 0.506$, $p = .004$), satisfying the sign condition for a U-shaped relationship. The estimated turning point, reported in Table 8, is 0.106 (95% CI [0.05, 0.15], $p < .001$), which lies within the observed UIS range ([0, 0.485]), confirming that the curvature is relevant to the data. The slope at the lower bound of UIS is negative (−0.107, $p = .062$) and only marginally significant, whereas the slope at the upper bound is positive (0.385, $p = .001$) and statistically significant at the 1% level. These results suggest an asymmetric U-shaped relationship, with stronger and more significant effects at higher levels of underperformance than at lower levels.

Table 8: Shape Condition Test Results

Wald Test	df	F	p value
H0: B1 = B2 = 0	(2, 9950)	6.34	.002*

Turning point [Min, Max)	Std. Error	CI 95%		p value
		Low	High	
0.106 [0, 0.485]	0.03	0.05	0.15	.000**

Slope Point	Effect	Std. Error	CI 95%		p value	
			Low	High		
Min	-0.107	0.06	-0.22	0.01	.062	
Max	0.385	0.12	0.15	0.62	.001	*

Comparison of Models (Hypothesis 2)

Comparing the two aspiration measures across equivalent model specifications reveals distinct patterns of influence on innovation output. In the linear models, UIH exhibits a positive and statistically significant effect (β1 = 0.055, p = .001) based on the same number of observations and clusters, indicating a stable positive association across the entire range of historical performance gaps. By contrast, UIS shows a positive but statistically insignificant coefficient (β1 = 0.032, p = .164), suggesting no reliable linear effect. This implies that, in purely linear terms, UIH exerts a stronger and more consistent influence than UIS.

In the quadratic specifications, the results are reversed. UIS demonstrates a significant positive quadratic term β2 = 0.506, p = .004) with a turning point within the observed range, and slope analysis confirms an asymmetric U-shape—with a strong positive effect at the upper extreme (0.385, p = .001) and only marginal significance at the lower extreme (-0.107, p = .062). Conversely, UIH quadratic model yields no statistically significant coefficients (β1 = 0.016, p = .642; β2 = .158, p = .151), providing no evidence of curvature. Therefore, while UIH dominates in the linear specification, UIS demonstrates a stronger and more complex influence in the non-linear specification, particularly when firms substantially outperform their social aspiration benchmarks.

The similarity in R-square and F-statistics across the UIH and UIS models indicates that both aspiration measures have comparable overall explanatory power for innovation output. This suggests that the difference between the two lies not in how much variance they explain but in the form and distribution of their effects. UIH exhibits a stable and statistically significant linear relationship, implying a consistent influence across the entire range of historical performance gaps. In contrast, UIS shows no significant linear effect but reveals a significant non-linear pattern, with a strong positive impact concentrated at high deviations from social aspirations. Thus, while both measures fit the data equally well in aggregate terms, UIH captures uniform changes in innovation output, whereas UIS captures more intense but asymmetric responses at the extremes of performance gaps.

Overall, the findings lend greater support to H2b, indicating that firms respond more strongly to deviations from social aspirations than from historical aspirations. While UIH exerts a stable and significant linear effect across the performance gap range, UIS generates a more intense—albeit asymmetric—response concentrated at extreme deviations, particularly when firms substantially outperform their industry peers. This pattern suggests that social comparison provides a more salient underperformance signal, triggering stronger innovation responses under conditions of large performance gaps.

Control Variables

Regarding the control variables, firm size exhibits a positive and statistically significant effect on innovation output across all model specifications, indicating that larger firms tend to generate more patents and trademarks, consistent with resource-based arguments that link greater scale to increased innovation capacity. In contrast, financial slack shows a negative and statistically significant association with innovation output, suggesting that excess uncommitted resources may reduce the urgency for innovation or be allocated to non-innovative activities. Firm age does not display a statistically significant relationship with innovation output in any specification, implying that organizational maturity, in isolation, is not a decisive factor in explaining innovation in this sample.

4.2 Robustness checks results

To ensure the reliability of the main findings, robustness checks were conducted in Stata with cluster-robust standard errors (CR2 correction), as outlined in Section 3.7.1. These checks test the stability of the results against alternative specifications, focusing on temporal robustness (three-period lag), distributional robustness (zero-inflated negative binomial model), Fixed-effect regression, and heterogeneity across firm sizes (subsample analysis). Results are summarized in Tables 9.a & 9.b.

Table 9a: Summary of Main and Robustness Results (UIH)

	Linear Model			Non Linear Model				
Model UIH	B1 Coef (p-value)	F-statistic/ X^2	R-square/ loglikeli -hood	B1 Coef (p-value)	B2 Coef (p-value)	Turning point	F-statistic/ X^2	R-square/ loglikeli -hood
Baseline (Pooled OLS, Lag2) *obs 57,706* *N 9951*	0.055 (.001)**	F(78,9950) 5.87**	0.0940	0.016 (.642)	0.158 (.151)	—	F(79,9950) 5.79**	0.0940

Model UIH	Linear Model B1 Coef (p-value)	F-statistic/ χ^2	R-square/ loglikeli-hood	Non Linear Model B1 Coef (p-value)	B2 Coef (p-value)	Turning point	F-statistic/ χ^2	R-square/ loglikeli-hood
Pooled OLS, Lag3 *obs 49,755* *N 9951*	0.037 (.050)*	F(78,9950) 5.80**	0.0931	-0.005 (.900)	0.172 (.161)	—	F(79,9950) 5.73**	0.0931
0ZINB (Count Part) *obs 59,706* *Nonzero obs 2,492* *N 9,951*	0.259 (.610)	*χ^2(79) 31,828*	-12887	-0.677 (.516)	3.918 (.248)	—	29,325	-12,886
Fixed-effect *obs 59,706* *N 9951*	-0.009 (.515)	F(8,9950) 4.81**	0.0072	-0.018 (.524)	0.032 (.731)	—	F(9, 9950) 4.28**	0.0070
Subsample: SMEs *obs 53,358* *N 8893*	0.029 (.027)*	F(75,8892) 5.92**	0.0477	-0.017 (.514)	0.185 (.044)*	0.046 (.375)	F(76,8892) 5.84**	0.0478
Subsample: Large Firms (Pooled OLS, Lag2) *obs 4740* *N 790*	-0.128 (.390)	F(50, 789) 2.69**	0.1730	0.222 (.472)	-1.403 (.133)	—	F(51, 789) 2.71**	0.1733

Table 9b: Summary of Main and Robustness Results (UIS)

Model UIS	Linear B1 Coef (p-value)	F-statistic/ χ^2	R^2/ loglikel-ihood	Non Linear B1 Coef (p-value)	B2 Coef (p-value)	Turning point	F-statistic/ χ^2	R^2/ loglikeli--hood
Baseline (Pooled OLS, Lag2) *obs 57,706* *N 9951*	0.032 (.164)	F(78,9950) 5.86**	0.0940	-0.016 (.062)	0.506 (.004)*	0.106 (.000)**	F(79,9950) 5.79**	0.0940

	Linear			Non Linear				
Model UIS	B1 Coef (p-value)	F-statistic/ χ^2	R^2/ loglikel-ihood	B1 Coef (p-value)	B2 Coef (p-value)	Turning point	F-statistic/ χ^2	R^2/ loglikeli--hood
Pooled OLS, Lag3 *obs 49,755 N 9951)*	0.015 (.526)	F(78,9950) 5.79**	0.0930	-0.110 (.064)	0.462 (.008)*	0.119 (.000)**	F(79,9950) 5.77**	0.0932
0ZINB (Count Part) *obs 59,706 Nonzero obs 2,492 N 9,951*	0.210 (.682)	*χ^2(79) 31,797*	-12887	-3.260 (.007)*	12.557 (.001)*	—	*χ^2(80) 31,107*	-12,880
Fixed -effect *obs 59,706 N 9951*	0.006 (.733)	F(8, 9950) 4.85**	0.0068	0.001 (.970)	0.016 (.900)	—	F(9, 9950) 4.33**	0.0067
Subsample: SMEs *obs 53,358 N 8893*	.034 (.050)*	F(75, 8892) 5.93**	0.0478	-0.037 (.325)	0.258 (.039)*	0.072 (.110)	F(76,8892) 5.86**	0.0479
Subsample: Large Firms (Pooled OLS, Lag2) *obs 4740 N 790*	-0.175 (.445)	F(50, 789) 2.71**	0.1732	-0.737 (.194)	2.084 (.206)	—	F(51, 789) 2.67**	0.1738

Three-Period Lag Specification

The Behavioral Theory of the Firm posits that firms may vary in the time they take to adjust their strategic actions in response to performance feedback, making it essential to assess the temporal robustness of the results (Greve, 2003). To examine whether the main findings are sensitive to the time lag specification, both Model 1 (UIH) and Model 2 (UIS) were re-estimated using a three-year lag for the independent variables, reducing the sample to 49,755 firm-year observations from 9,951 clusters.

For UIH, the three-year lag model shows a smaller but still positive and statistically significant linear coefficient (β1=0.037,p=.050), consistent with the baseline two-year lag results, and again no evidence of a non-linear relationship (β2=0.172,p=.161). For UIS, the linear term in the linear specification remains insignificant (β1=0.015, p=.526). In the quadratic specification, the linear term has a negative sign and is marginally significant (β1=-0.110, p=.064), and the quadratic term retains its positive sign and significance (β2=0.462, p=.008), with the significant turning point located within the observed data range, confirming the asymmetric U-shape pattern.

This confirms the temporal robustness of the key results. The positive linear effect of UIH is consistent across lag structures, supporting H1a for historical aspirations. The asymmetrical U-shaped relationship for UIS remains intact, partially supporting H1c for social underperformance. These findings provide stronger evidence for H2b (greater sensitivity to social aspirations).

Zero-Inflated Negative Binomial (ZINB) Model

The high proportion of zero observations in innovation output (95%, with only 2,492 out of 59,706 observations having nonzero values) raises concerns about the appropriateness of the OLS model, making it necessary to test distributional robustness (Cameron & Trivedi, 2013). To account for the excess zeros and the count nature of the dependent variable, both Models 1 (UIH) and 2 (UIS) were re-estimated using a zero-inflated negative binomial (ZINB) specification.

For UIH (Model 1), the linear specification yields a positive but statistically insignificant count-part coefficient (β1=0.259, p=.610), indicating that the significant positive linear effect observed in the baseline OLS model does not hold under ZINB. In the nonlinear specification, both the linear (β1=−0.677, p=.516) and quadratic terms (β2=3.918, p=.248) are insignificant, providing no evidence of curvature. These results weaken the support for the baseline UIH findings, suggesting sensitivity to model specification.

For UIS (Model 2), the linear specification also produces an insignificant coefficient (β1=0.210, p=.682), consistent with the baseline OLS where no linear effect was detected. In the nonlinear specification, the linear term becomes negative and statistically significant (β1=−3.260, p=.007), while the quadratic term remains positive and significant (β2=12.557, p=.001). The significant turning point is located within the observed data range, reinforcing the presence of an asymmetric U-shaped relationship. The magnitude of the coefficients in the ZINB model is larger than in the OLS estimates; however, this difference reflects the change in estimation method and scale (log-count in ZINB) rather than a substantively stronger effect.

Under ZINB, the positive linear effect of UIH in OLS disappears, weakening support for H1a, while the asymmetric U-shaped relationship for UIS remains statistically significant and consistent in form, partially reinfo H1c and providing stronger support for H2b. Larger coefficients in ZINB reflect model scale differences rather than stronger substantive effects.

Firm Fixed Effects

To further assess the robustness of the baseline findings, a fixed effects OLS model was estimated to address potential bias from unobserved, time-invariant firm characteristics that pooled OLS cannot separate. By exploiting only within-firm variation over time, this approach controls for all firm-specific factors that remain constant during the sample period. Results indicate that neither UIH nor UIS is statistically significant in either the linear or the non-linear specifications (Tables 9.a and 9.b). The explanatory power of the fixed effects models is extremely low (R-square ≈ 0.0007), suggesting that within-firm variation in performance feedback over time explains very little of the variation in innovation output. These results provide no evidence to support any of the hypotheses and indicate that, once firm-specific fixed characteristics are controlled for, the relationship between underperformance and innovation output is negligible. A possible explanation for this might be the relatively short panel period and the persistence of key variables (such as underperformance) over time.

Subsample Analysis: SMEs vs. Large Firms

Firm size may moderate responses to performance feedback, as smaller firms may be more sensitive to underperformance (Audia & Greve, 2006). To test for heterogeneity, subsample analyses were conducted separately for SMEs (employees < 250 & total assets < 43 mil euros) (53,358 observations, 8,893 firms) and large firms (4,740 observations, 790 firms).

SMEs

For the SME subsample (N = 53,358; 8,893 clusters), the linear specification yields a positive and statistically significant coefficient of UIH ($\beta 1=0.029, p=0.027$), indicating that higher underperformance relative to historical aspirations is associated with greater innovation output. In the non-linear specification, the quadratic term is positive and statistically significant ($\beta 2=0.185, p=0.044$), while the linear term becomes insignificant. Furthermore, the explanatory power of both models is identical (R-squares are 0.0477 & 0.0478), and the F-statistic is slightly higher in the linear model than in the non-linear model. Given the lack of improvement in model fit and the insignificant turning point, the results indicate no robust evidence of curvature, and the linear model is preferred following the parsimony principle (Burnham & Anderson, 2002; Box & Jenkins, 1976).

In the linear specification, UIS has a positive and statistically significant coefficient ($\beta 1=0.034, p=0.050$), suggesting that higher underperformance relative to social aspirations is associated with greater innovation output. In the non-linear specification, the linear term becomes negative and insignificant ($\beta 1=-0.037, p=0.325$), while the quadratic term is positive and statistically significant ($\beta 2=0.072, p=0.039$). Similar to UIH, the estimated turning point is not statistically significant. Both models have the same explanatory power, and the F-statistic is slightly higher for the linear model. Given the lack of improvement in model fit and the insignificant turning point, the evidence does not support a robust asymmetric U-shaped relationship, and the linear model is preferred following the parsimony principle.

Large firms.

For large firms (N = 4,740; 790 clusters), no relationship is found between either UIH or UIS and innovation output in both linear and non-linear specifications, with all coefficients statistically insignificant (see Tables 9.a and 9.b).

Comparing the SME and large-firm subsamples reveals clear differences in the role of performance feedback. For SMEs, UIH shows a positive and statistically significant linear effect, consistent with H1a and the baseline results, while UIS also exhibits a positive linear association, albeit with weaker statistical significance. In contrast, for large firms, neither UIH nor UIS is statistically significant in either linear or non-linear specifications, despite the models having higher explanatory power (R-square = 0.1733 & 0.1738, respectively) than in the baseline.

In summary, with the subsample analysis, SMEs and large firms show clear differences. SMEs respond to underperformance when both UIH and UIS have positive linear effects, although the effect of UIS is less stable, suggesting that SMEs are more sensitive to underperformance situations. SMEs support hypothesis H1a for both UIH and UIS. In contrast, large firms do not show any statistically significant relationship between UIH/UIS and innovation output, suggesting that innovation in this group is influenced by factors other than performance feedback.

4.3 Final Results

The empirical analyses reveal distinct patterns for the two aspiration reference points.

For historical aspirations, the baseline pooled OLS model indicates a positive and statistically significant linear relationship with innovation output, while the quadratic term is not significant. This pattern persists in the three-period lag specification and in the SME subsample but disappears in alternative models such as ZINB and fixed effects, suggesting that the effect is unstable across specifications. Large firms show no significant relationship. These findings provide partial and context-dependent support for H1a (positive linear effect) but no evidence for a non-linear effect.

For social aspirations, results consistently show an asymmetric U-shaped relationship: severe underperformance is associated with increased innovation, whereas mild underperformance corresponds to weaker or negative responses. This pattern remains robust in the three-period lag model and ZINB, but disappears under fixed effects. In SMEs, UIS also exhibits a positive linear association, though the evidence for curvature is weaker; in large firms, no significant effect is detected. These results partially support H1c (non-linear effect) in the form of an asymmetric U-shape.

When comparing the two measures (H2), UIH exerts a stable linear effect, while UIS has no clear linear influence but shows a stronger, non-linear pattern concentrated at extreme gaps. Both measures explain a similar proportion of variance in innovation output, but their forms of influence differ: UIH reflects uniform changes across the range, whereas UIS captures more intense responses at the extremes. This provides greater support for H2b, indicating higher sensitivity to social aspirations under large deviations.

Overall, the evidence suggests that: 1) UIH → Positive linear effect, limited robustness (H1a). 2) UIS → Robust asymmetric U-shaped effect, driven by severe underperformance (partially H1c). 3) Firms are generally more responsive to large social performance gaps than to historical ones (H2b)

CHAPTER 5: DISCUSSION & CONCLUSION

5.1 Discussion of results.

Effects of Underperformance Relative to Historical Aspirations

Underperformance relative to historical aspirations exhibits a positive linear association with innovation output in the baseline pooled OLS model, consistent with the Behavioral Theory of the

Firm's view that performance gaps can trigger problemistic search. However, this effect is not supported by the nonlinear specification and disappears in alternative estimations (FE, ZINB), indicating that it is context-dependent rather than systematic. The relationship persists among SMEs—likely due to greater organizational flexibility and learning capacity—but is absent in large firms, possibly reflecting strategic inertia and resource slack.

From a theoretical perspective, BTOF (Cyert & March, 1963) posits that performance gaps may be interpreted as challenges, stimulating search for solutions (Greve, 2003; Ren et al., 2024). Conversely, the Threat-Rigidity perspective (Staw et al., 1981) predicts that underperformance perceived as a threat can narrow search and reduce innovation (Audia & Greve, 2006; Chen & Miller, 2007). The absence of a negative effect for UIH suggests that, in this context, historical underperformance is not viewed as a severe failure.

Following the conceptual framework, HA is typically perceived as an internal benchmark, comparing current performance with the firm's own history. Such signals are familiar and often seen as adjustable through internal process improvements, making them less likely to trigger strong threat perceptions than externally driven comparisons. Managers may interpret these gaps as technical or operational challenges rather than strategic crises, reducing defensive reactions and enabling solution-oriented responses. Motivation to innovate thus emerges as a means to restore expected performance, particularly when the problem is seen as solvable.

According to Yu et al. (2019), historical aspirations represent an internal performance signal, the interpretation of which depends on managers' subjective evaluations and can therefore be adjusted or delayed. In contrast, the results of this study show a significant effect of historical underperformance on innovation, suggesting an alternative explanation. One possible interpretation is that managerial responses to internal signals may also be shaped by contextual factors such as macroeconomic conditions or a cultural predisposition toward innovation. In the Flemish context, the innovation-friendly environment may facilitate the translation of motivation from underperformance into concrete innovation activities. Flanders ranks as a Strong Innovator in the Regional Innovation Scoreboard, and Belgium scores highly on the International Property Rights Index (Property Rights Alliance, 2019). As highlighted by Dodgson et al. (2014), such conditions—including strong institutional support, R&D-oriented policies, and well-developed knowledge linkages—create a fertile environment for converting the motivational trigger of underperformance into tangible innovation outputs.

Overall, the findings support the Behavioral Theory of the Firm, indicating that historical underperformance can stimulate innovation, particularly in contexts—such as Flanders—where strong institutional support and an innovation-oriented culture facilitate the translation of motivation into action

Effects of Underperformance Relative to Social Aspirations

The results indicate an asymmetric U-shaped relationship between underperformance relative to social aspirations and innovation output. Severe performance gaps with industry peers are linked to substantial increases in innovation, whereas mild gaps are associated with weaker or even negative innovation responses. This suggests that competitive pressure can encourage risk-taking and innovation when deficits are large, but may prompt caution or retrenchment when the gap is small.

Social aspiration gaps are highly salient because they arise from direct comparisons with competitors, making them difficult to overlook. In competitive environments, such signals are less controllable and closely tied to relative position and reputation, exerting a strong influence on managerial evaluations. The response appears to hinge on perceived severity: mild gaps are often seen as temporary setbacks rather than crises, creating reputational or growth concerns rather than survival threats. In such cases, firms may adopt defensive or risk-averse strategies, consistent with the Threat-Rigidity Theory (Staw et al., 1981), which predicts reduced investment in high-risk innovation. Empirical evidence from Guo and Ding (2017) supports this view, showing that mild gaps tend to be associated with lower risk activities.

By contrast, severe gaps may be interpreted as strategic challenges, triggering problemistic search (BTOF; Cyert & March, 1963) and encouraging risk-taking to pursue radical solutions. Prior studies (Baum et al., 2005; Yu et al., 2019) similarly find that strong competitive pressure can stimulate radical innovation even under resource constraints. In the Flemish context—where innovation is a key growth driver—severe gaps can create strategic urgency due to their impact on reputation and competitive position, making innovation a means to restore standing.

These findings differ from Liu et al. (2024) and Su et al. (2023), who report that severe underperformance often shifts firms from aspirations to survival, leading to defensive behavior and an inverted U-shape. In this study, the transition from defensive to innovative responses appears to occur at a relatively low threshold. The pattern resembles a right-skewed asymmetric U-shape, with stronger effects under severe underperformance. There is limited evidence of survival threat, and the results may be better explained by reputation-based considerations. This interpretation is consistent with Lucas et al. (2018), who argue that managers may respond with innovation to protect their personal and professional reputation, in line with the BTOF. In the present context, however, managers may adopt more conservative strategies to safeguard their reputation, reflecting the Threat–Rigidity perspective. This contrast underscores the subjective nature of managerial interpretations of underperformance signals.

The subgroup analysis reveals notable differences between SMEs and large firms. These results challenge the assumptions of the conceptual framework by showing that resource endowments, organizational scale, and managerial confidence can moderate how underperformance signals are interpreted.

For SMEs, underperformance triggers stronger innovation responses, reflecting faster learning, greater organizational flexibility, and higher creative capacity (Rosenbusch et al., 2011). Falling behind peers may directly threaten SMEs' competitive viability and collaborative opportunities, creating stronger incentives to innovate.

Large firms, by contrast, often exhibit strategic inertia due to organizational complexity, while abundant resources may foster complacency and delay strategic change (Todeva, 2007). They also benefit from brand loyalty and stable market positions, which reduce competitive pressure and weaken responsiveness to performance gaps.

Taken together, these reactions—regardless of whether the performance gap is historical or social—indicate that SMEs are generally more sensitive to underperformance. In SMEs, both internal and external pressures appear to simultaneously stimulate innovation, whereas large firms are less responsive in either case.

Overall, these findings suggest that underperformance relative to social aspirations exerts an asymmetric, nonlinear influence on innovation: severe gaps stimulate innovation, while mild gaps are linked to limited or negative responses. This highlights the salience of external social benchmarks in shaping innovative behavior and offers context-specific empirical support for RQ1.

Comparing Sensitivity to Historical and Social Aspiration Signals

The results indicate that both UIH and UIS can stimulate innovation under severe underperformance, but responses diverge when the performance gap is small. For UIH, even minor gaps are associated with increased innovation, consistent with the Behavioral Theory of the Firm (Cyert & March, 1963), which posits that any deviation from historical aspirations is perceived as a problem requiring corrective action. In the favorable innovation environment of Flanders and Belgium—with strong R&D support and extensive public–private collaboration—such gaps may be more readily translated into innovation initiatives.

In contrast, for UIS, small gaps tend to trigger more conservative behavior and reduced innovation. Threat-Rigidity Theory (Staw et al., 1981) suggests that competitive comparisons under mild underperformance can induce risk aversion, leading firms to prioritize defensive measures over innovation. From the perspective of March & Shapira (1992), firms focus on the goal closest to current performance—either the aspiration level or the survival point. The low turning point for UIS in this study suggests that competitive pressure and reputational concerns, rather than survival threats, drive the response. In Belgium's innovation-intensive and collaborative context, even a small disadvantage relative to peers can prompt caution or short-term retrenchment.

Subsample analysis shows that SMEs respond linearly to both UIH and UIS, indicating that they interpret historical and social aspiration gaps in similar ways. Their reactions, however, reveal a stronger emphasis on internal benchmarks, as underperformance relative to their own past performance is perceived as a direct signal of operational inefficiency that can be addressed through internal changes. At the same time, gaps relative to social aspirations exert more intense pressure, as falling behind peers threatens SMEs' competitive position and collaborative opportunities, prompting a faster and more proactive search for innovation. Large firms, by contrast, show no significant reaction to either measure, likely due to resource abundance, stable market positions, and greater organizational inertia.

The results also indicate that firm size is positively and linearly associated with innovation output, suggesting that larger firms generally generate more innovation. When combined with the subgroup analysis, this implies that large firms, while capable of producing more innovation overall, do not necessarily respond strongly to underperformance signals alone. Organizational context and resource abundance may dampen the urgency to act, leading to slower or weaker reactions. This aligns with Audia and Greve's findings that large firms tend to react less, or more slowly, to underperformance due to managerial confidence and the structural complexity of their organizations.

In contrast to firm size, slack shows the opposite pattern. High slack is associated with lower innovation output, consistent with Lu and Wong (2019), who argue that high slack fosters managerial confidence and reduces pressure, thereby lowering risk-taking propensity. Low slack, on the other hand, creates stronger motivation to innovate. In Flemish, government support and favorable policy conditions may further encourage innovation even when slack is limited. Moreover, the country's open innovation environment enables firms to share resources such as knowledge and financing, helping them overcome the constraints of low slack.

Finally, firm age shows no significant effect on innovation, suggesting that innovation capacity in Belgium is not confined to market experience. Younger firms and start-ups can be equally innovative, with performance depending more on firm-specific motivation than on longevity.

5.2. Contribution

This study offers four interrelated contributions to the performance feedback–innovation literature.

First, from a methodological standpoint, it operationalizes innovation through output indicators—patents and trademarks—rather than the more commonly employed input measures such as R&D expenditure or intensity. These output-based indicators capture realized innovation outcomes in addition to the underlying intention to innovate, thereby providing a more outcome-oriented perspective. Furthermore, the analysis employs both linear and nonlinear model specifications for historical and social aspirations. The contrasting patterns observed—positive linear for historical aspirations and asymmetric U-shaped for social aspirations—demonstrate that reliance on a single specification risks obscuring important heterogeneity in firm responses, underscoring the value of adopting multiple specifications in performance feedback research.

Second, the findings contribute to theory by clarifying how the source and severity of performance gaps are associated with innovative activity. These patterns suggest that reputational and competitive considerations may exert greater influence in responses to social aspiration gaps, while reactions to historical aspiration gaps may be more strongly shaped by internally oriented interpretations.

Third, the study provides empirical evidence based on a large and diverse panel dataset encompassing both SMEs and large firms across multiple industries. This breadth enables a more generalizable account of how organizations respond to underperformance, without restricting the analysis to a single sector or firm size category.

Finally, by situating the analysis in Belgium and Flanders—regions characterized by strong intellectual property protection, dense collaborative R&D networks, and supportive innovation policies—the study extends the empirical evidence on performance feedback and innovation to an innovation-driven regional context. Although contextual effects are not directly tested, these institutional features form an important backdrop for interpreting the observed patterns of firm behavior.

5.3. Managerial Implications

The empirical findings suggest several avenues through which managers can translate performance feedback into innovation strategies. Underperformance relative to historical aspirations, which in this study shows a positive linear association with innovation output—particularly among SMEs—can serve as an early-warning signal that prompts timely action. Even modest declines from past performance, if identified promptly, can justify the initiation of innovation projects before problems escalate. This requires the integration of historical benchmarks into regular performance monitoring, ensuring that trend analyses directly inform resource allocation decisions. For example, internal performance reviews could be linked to stage-gate checkpoints in product development or process improvement, enabling firms to commit resources to innovation while the performance gap is still manageable.

For social aspirations, the results indicate that the nature of the response depends on the magnitude of the gap. When the shortfall relative to peers is large, managers may need to pursue more substantial and potentially riskier innovation activities, such as developing new technologies or launching products that clearly differentiate the firm in the marketplace. When the gap is small, however, more measured actions—incremental improvements, operational efficiencies, or targeted brand adjustments—may be sufficient to address reputational concerns without incurring excessive risk.

The Flemish context, characterized by strong intellectual property protection, targeted policy support, and dense collaborative R&D networks, provides a favorable environment for implementing such strategies. Firms can draw on established partnerships and knowledge-sharing platforms to enhance innovation capacity and align outputs with strategic objectives. In practice, this could involve prioritizing patents when pursuing long-term technological goals, or focusing on trademarks when rapid market repositioning is required.

Firm size also shapes how performance feedback translates into innovation behavior. SMEs, with their greater flexibility and faster learning cycles, appear more responsive to both historical and social performance gaps. They can strengthen this responsiveness by leveraging external funding sources, shared infrastructure, and collaborative networks to overcome resource constraints. Large firms, in contrast, may need to address structural and procedural inertia to respond effectively to performance shortfalls. Streamlining decision-making processes and regularly reassessing aspiration benchmarks can help ensure that innovation efforts remain aligned with changing market conditions.

5.4. Limitations and Future Research

Methodological Considerations

While this study makes several methodological contributions, it is not without limitations.

First, the operationalization of innovation as the combined number of patents and trademarks, while capturing tangible outputs, may underestimate the full scope of innovative activities. Some innovations—particularly incremental process improvements, organizational innovations, or informal product modifications—may not be patented or trademarked, leading to potential measurement bias.

As a result, the findings primarily reflect formal, legally protected innovations rather than the broader spectrum of innovation outputs.

Second, the use of patents and trademarks as innovation proxies inherently involves time lags between the decision to innovate and the formal registration of outputs. Although lag structures were applied to mitigate this issue, the fixed lag periods may not perfectly align with the varying innovation cycles across firms and industries, introducing temporal mismatch and potential attenuation of observed effects.

Third, the study focuses on Flemish firms within a specific period (2014–2019), which offers a unique socio-economic and policy environment but may limit the generalizability of the results to other contexts. The innovation-supportive institutional setting in Flemish—characterized by strong IP protection and collaborative networks—may amplify or dampen certain behavioral responses to underperformance compared to countries with less developed innovation ecosystems.

Fourth, the methodological design relies on panel regression models with aspiration levels operationalized through historical and industry benchmarks. While this approach controls for observed firm characteristics and unobserved heterogeneity to some extent, the use of pooled OLS for panel data does not disentangle within-firm effects (changes over time within the same firm) from between-firm effects (differences across firms). This limits the ability to fully identify whether the observed relationships are driven by temporal adjustments within firms or by structural differences between firms. In addition, the operationalization of aspirations assumes comparability of benchmarks over time and across firms, which may not hold in the presence of major macroeconomic shifts or industry composition changes. Endogeneity concerns also remain, such as reverse causality between innovation and performance, or omitted variable bias arising from unobserved strategic or managerial factors.

Finally, the linear and quadratic specifications used to test for nonlinearities offer an interpretable functional form but may oversimplify complex relationships. Alternative modeling approaches—such as spline regressions or threshold models—could provide a more flexible representation of how performance gaps influence innovation across different ranges.

Theoretical Refinements

The contrasting patterns observed for historical and social aspirations add important nuance to existing theories of performance feedback and innovation. In the case of historical aspirations, the consistent positive association between underperformance and innovation aligns with the Behavioral Theory of the Firm (BTOF), yet the results indicate that this relationship holds even for small performance gaps. This suggests that BTOF's prediction of problemistic search applies broadly to internal benchmarks, where deviations are interpreted as signals for corrective action without triggering excessive risk aversion.

For social aspirations, the asymmetric U-shaped pattern reveals a different mechanism. Severe underperformance stimulates innovation, whereas mild underperformance is associated with defensive or risk-averse responses—consistent with the Threat-Rigidity perspective. These results expand the scope of Threat-Rigidity Theory by showing that such responses can arise from reputational and competitive concerns rather than survival threats alone. The low turning point identified in the analysis also challenges the Shifting Focus Model (March & Shapira, 1992), suggesting that firms may shift from defensive to innovative strategies at smaller competitive gaps than the model anticipates, especially in collaborative and reputation-sensitive environments such as Belgium's innovation ecosystem.

The findings further highlight the role of organizational capabilities. The stronger responsiveness of SMEs to both aspiration types points to the advantages of flexibility and adaptive learning in acting upon performance feedback, even under resource constraints. In contrast, the inertia often observed in large firms suggests that abundant resources do not automatically translate into greater responsiveness, particularly when innovation outputs such as patents and trademarks require sustained commitment and longer time horizons.

Future Research Directions

Building on the limitations and theoretical refinements outlined above, several promising directions emerge for future research.

First, extending the measurement of innovation beyond patents and trademarks would capture a broader spectrum of innovative activities. While formal IP-based measures reflect tangible, legally protected outputs, they overlook non-patented process, organizational, and digital innovations. Incorporating survey-based measures or innovation survey data (e.g., CIS) could reveal whether the asymmetric effects observed for social aspirations persist across different innovation types.

Moreover, addressing the temporal dynamics of innovation could deepen understanding of performance feedback mechanisms. Future studies could employ longer panel datasets to better capture within-firm changes over time, enabling a clearer distinction between short-term adaptive responses and long-term strategic shifts. Variable lag structures or distributed lag models could also account for industry-specific innovation cycles, reducing temporal mismatch between performance feedback and innovation outcomes.

Furthermore, future work could explore alternative nonlinear modeling techniques—such as spline regressions, piecewise linear models, or threshold regressions—to more flexibly detect and estimate turning points in the aspiration–innovation relationship. This would help verify the robustness of the asymmetric U-shaped pattern for social aspirations and test whether historical aspirations exhibit similar nonlinearity in other contexts.

In addition, the cross-sectional and contextual boundaries of the findings merit further investigation. Expanding the analysis to cross-country or cross-industry samples would reveal whether the asymmetric U-shape for social aspirations is a universal pattern or a product of Belgium's innovation-supportive ecosystem. Comparative studies could assess how differences in institutional quality, IP protection, and collaborative networks moderate the performance feedback–innovation link.

Finally, examining the role of managerial cognition and strategic decision-making directly—through qualitative interviews, experimental designs, or text analysis of corporate communications—could validate the proposed interpretation pathways (perception → interpretation → motivation →

capability). Such research could clarify whether reputational concerns, survival threats, or other cognitive frames are the primary drivers of the asymmetric innovation response to social underperformance.

By addressing these areas, future research can further refine theoretical models, strengthen causal inference, and improve the practical relevance of performance feedback theory in innovation strategy.

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