NBS Working paper

18/2025

Why do SMEs not Apply for Loans?

Bank Loan Application Behavior and Access to Finance in the Euro Area

Florian Horky, Jarko Fidrmuc, Jan Klacso, Reiner Martin

NATIONAL BANK OF SLOVAKIA
EUROSYSTEM

www.nbs.sk

Publisher

research@nbs.sk

Contact
National Bank of Slovakia
Imricha Karvaša 1
813 25 Bratislava

Electronic version
https://nbs.sk/en/publications/research-papers-working-and-occasional-papers-wp-op/

ISSN 2585-9269 (electronic version)

Why do SMEs not Apply for Loans? Bank Loan Application Behavior and Access to Finance in the Euro Area*

Florian Horky[a], Jarko Fidrmuc[b], Jan Klacso[c], Reiner Martin[d]

Abstract

Non-application behavior for bank loans among European SMEs is economically more prevalent than loan application rejections by banks. Therefore, it should not be treated as a residual state but disentangled by its different reasons. Using microdata from the Survey on the Access to Finance of Enterprises (2014–2025), we document how firms choose and switch between loan application, discouragement, reliance on internal funds, and other non-application reasons. We combine an expected-utility framework with empirical estimations through multinomial and standard logit models. The main novelty is our ability to simultaneously investigate different types of non-application for bank loans, which are driven by differing forces. Discouragement manifests as a belief-driven channel of non-application, loan costs and the supply side drive another, cost-driven channel of non-application. By disentangling driving forces of non-application for bank loans as core element of the analysis, our study provides new evidence on why SMEs choose not to apply for bank loans. We highlight that these decisions can reflect diverse and contradictory underlying conditions. Our results are important for understanding and addressing these differing driving forces of SMEs bank loan application behavior.

JEL codes: D22, E51, F33, G21

Keywords: access to finance, SMEs, bank loans, monetary policy, regulatory policy, corporate finance, bank lending

---

* Acknowledgements: We strongly profited from comments provided by Steven Ongena, Stelios Giannoulakis, Dimitrious Anastasiou, Camelia Turcu, Marcel Voia and Roman Horvath. We further thank the ECMI I NBS I CEPS I SUERF Research Conference 2025 participants and especially our discussant Annalisa Ferrando for questions and comments. Moreover, we would like to thank participants of research workshops at the European Research University in Prag (2025), the Laboratoire d'Économie d'Orléans - LEO (2025) and the Zeppelin University in Friedrichshafen (2025) for their comments and fruitful discussions. The views expressed are the authors' and not necessarily the ones of the Slovak National Bank or the Eurosystem.

[a] National Bank of Slovakia, Zeppelin University
[b] Zeppelin University
[c] National Bank of Slovakia
[d] National Bank of Slovakia

Non-technical summary

Small and medium-sized enterprises (SMEs) are the backbone of the European economy, accounting for more than half of EU GDP and almost two-thirds of private-sector employment. Yet, many SMEs limit their own potential external financing, because they choose not to apply for bank loans. Understanding this non-application behavior is essential for designing policies that effectively support business investment and growth. Across our sample, using the *Survey on the Access to Finance of Enterprises (SAFE)*, **5.4 percent** refrain from applying because they expect rejection or face discouragement for other reasons, and **21.2 percent** do not apply for other reasons. Compared to only about **2.2 percent** of firms experiencing an outright loan rejection, these numbers imply that self-exclusion from the credit market is much more common than formal rejection. Non-application is therefore not a marginal phenomenon, it represents a major, and often inefficient, source of under-investment in Europe's SME sector.

Traditional analyses tend to treat non-application as a residual category. Our study assumes that this view is incomplete and does not sufficiently capture heterogeneous drivers of non-application behavior. We develop an *expected-utility framework* in which the firm weighs the expected benefits and costs of applying for a loan given its fundamentals, perceptions, and the external credit environment. This semi-structured perspective allows us to distinguish *why* firms decide not to apply and to link these motives to measurable firm and market characteristics. Based on this framework, we identify four options that jointly shape SME financing behavior:

- **Application**: The firm actively applies for a loan.
- **Internal funds**: The firm has sufficient liquidity/own funds and self-finances investment.
- **Discouragement**: The firm refrains from applying because it expects rejection or sees little chance of success (a belief-driven channel).
- **Other reasons**: The firm does not apply due to perceived high borrowing costs or administrative frictions (a cost-driven channel).

We complement our mechanism evaluation by multinomial and standard logit models with SAFE microdata, and a constructed supply-side indicator from the ECB's Bank Lending Survey. The findings are robust across pre-COVID, COVID, and post-COVID periods. Larger, older, and more profitable firms with clear investment plans are more likely to apply for loans, while small and young firms apply less frequently—a gap that widened after the pandemic. Negative perceptions of loan availability strongly increase the likelihood of discouragement. Positive past experiences with bank loans foster persistence in applying, revealing a "perception channel" that links beliefs and learned experiences to credit demand. Refinancing needs also heighten discouragement, reflecting weaker fundamentals. Non-application for "other reasons" is associated with perceived costs and tighter credit supply, a pattern that became more pronounced after the recent interest-rate hikes. Overall, discouragement and cost-related non-application are shown to be economically distinct behaviors.

Our results highlight that non-application behavior has different reasons. To limit its inefficient component, predictable and transparent lending conditions are crucial. Even modest tightening of supply conditions can substantially raise discouragement rates, especially among smaller firms. Targeted policies can make a difference. For instance, reducing application costs, as demonstrated by Belgium's 2014 reform studied by Ferrando & Mulier (2022), can encourage more firms to apply. Similarly, public guarantee schemes, improved feedback mechanisms between banks and SMEs, and clear communication of lending standards can offset negative perceptions and prevent persistent self-exclusion. Ultimately, the paper shows that SME access to finance is shaped by objective balance-sheet constraints but also by beliefs, expectations, and past experiences. Recognizing and addressing these behavioral dimensions can improve credit allocation efficiency and enhance the resilience of Europe's SME sector.

1. Introduction

Small and medium-sized enterprises (SMEs) are prone to self-imposed credit constraints due to not applying for bank loans although they are likely to qualify for a loan (Ferrando & Mulier, 2022). This can have detrimental effects for investment, economic growth, and employment in Europe, given that SMEs account for 52% of European Union (EU) GDP and 64% of all jobs in the private sector (Eurostat, 2022). Bank finance and the use of own resources are often the only available financing options for EU SMEs, given that capital markets tend to be significantly less developed in the EU than for example in the US.[1]

Previous loan rejections are one of the reasons that often discourage firms from further loan applications, even if they would possibly qualify for a loan (Berg, 2018, Ferrando & Mulier, 2022). Across our sample, however, only about 2.2% of firms experience an outright loan rejection, while 5.4% refrain from applying because of discouragement for other reasons and 21.2% do not apply for reasons that are unrelated to discouragement. This pattern confirms that non-applications are quantitatively much more important than loan rejections, a finding that is consistent with the motivation of Ferrando and Mulier (2022).

The economic implications are substantial. SMEs that apply for a bank loan are more than twice as likely to invest compared to discouraged firms or those abstaining from loan applications for other reasons.[2] In this study we therefore focus on non-application for bank loans. Using SAFE microdata for the euro area (2014–2025), we document how SMEs switch among different bank loan application states, i.e. ‘Application’, ‘Discouragement’, ‘Use of internal funds’, and ‘Other non-disclosed reasons for non-application’. We further show how the dynamics between these application states change across pre-COVID, COVID, and post-COVID/interest-rate hike regimes. For this purpose, we develop an expected-utility framework to interpret choices and quantify the relative importance of firm characteristics, needs, performance, supply-side conditions, and behavioral factors. Additionally, we estimate (multinomial) logit models to empirically assess SMEs behaviors.

The existing literature sheds light on various aspects of SME financing and the reasons for the heterogeneity in access to finance. For instance, the credit screening process is often based on superficial characteristics such as firm size or age and fails to capture the true solvency of smaller enterprises, leading to excessively restrictive access to finance (Sharpe 1990; Andrieu et al., 2018). Moreover, loan rejections can foster a perception among firms that lending policies are more restrictive than they are in reality, discouraging future loan applications (Fidrmuc et al., 2023, Horky & Fidrmuc, 2023). Past financial performance (Orgler, 1970) and the role of collateral and personal securities (Hernández-Cánovas & Martínez-Solano, 2010) are also highly relevant when it comes to SMEs’ financing. By contrast, business prospects are at times insufficiently taken into account (Andrieu et al., 2018). To provide a foundation for our research, we sort the literature into three major streams relevant for our analysis.

In the first stream of literature, the role of firm characteristics such as size, age, and sectoral engagement has been extensively investigated. This literature typically builds on theories of capital structure, such as Hackbarth et al. (2007), who extend the trade-off theory to debt structure and highlight how asymmetric information and default risk shape firms’ financing constraints. Connected to the general idea of debt structure considerations, Kon & Storey (2003) provide a seminal theoretical foundation for understanding discouraged borrowers, i.e. firms that do not apply for bank credit even when potentially eligible. Their model formalizes how expectations

[1] The EU institutions are strongly motivated to create a single market for capital, facilitating the flow of investments and savings. This should benefit companies and support economic recovery, job creation, and the EU’s green and digital agendas. Considering the European SME landscape, developing a more dynamic market for creating and placing SME credit as securities could be a helpful avenue to free up banks’ balance sheets for lending (Véron & Wolff, 2016). Moreover, young and high-growth SMEs could potentially benefit from easier access to basic financing via a unified European capital market.

[2] The values are calculated based on the SAFE survey. The numbers and statements are further deepened and explained in our data and stylized facts sections in the paper.

of rejection or excessive costs can lead to subsequent non-application, turning discouragement into a form of credit rationing. Empirically, this line of reasoning has been extended by a multitude of studies. It is generally found that SMEs and young firms are more likely to be discouraged from loan applications (Chakravarty & Xiang, 2013). This effect of firm size is confirmed by Fidrmuc & Horky (2023), who observe that small firms exhibit a higher propensity to be discouraged compared to medium and large firms. Considering firm size, Fidrmuc et al. (2024) further argue that in smaller firms, the owner-managers often negotiate directly with banks, a situation less common in larger firms. This may contribute to the heterogeneity in perceived bank loan availability across firm size. As for firm age, the literature presents a less conclusive picture. Fidrmuc & Horky (2023) find, that particularly young firms are more likely to be discouraged. This aligns with Chakravarty and Xiang (2013), who demonstrate that non-discouraged firms tend to be significantly older than their discouraged counterparts and that firm age has a significant influence on the likelihood of discouragement. Cavalluzo et al. (2002) offer a potential rationale for this, underscoring the significance of a firm's previous credit history in securing successful financing. Access of SMEs to finance is significantly influenced by their credit ratings, which serve as a crucial indicator of creditworthiness for lenders. SMEs with higher credit ratings have better access to bank loans due to perceived lower risk (Berger & Udell, 2006). However, firm characteristics heavily influence this access, as SMEs often face challenges in obtaining favorable credit ratings due to limited financial histories and collateral, corresponding to the firm age aspect (Beck et al., 2008). Additionally, smaller firms typically receive lower ratings, which constrains their ability to secure necessary funds (Canton et al., 2013). Sectoral aspects also play a prominent role for access to finance. Coluzzi et al. (2015) argue that these differences reflect differences in firms' asset structure, which might be relevant for collateral considerations. Fidrmuc et al. (2024) also confirm small deviations across sectors when it comes to beliefs about bank lending policy. In addition to firm-fixed characteristics, other enterprise-specific aspects are also important. One such aspect is past financial performance. Orgler's model for credit scoring of commercial loans (1970) underscores the importance of profitability and liquidity as indicators of a firm's capacity to repay a loan. Contrasting this view with empirical evidence, Chittenden et al. (1996) emphasize that less profitable firms tend to resort to loans by providing collateral, while profitable firms are more likely to utilize internal funds, which might prevent them from investing. De Marzo et al. (2008), offer a theoretical extension of the *q* theory of investment, highlighting the significance of firms' past profitability on current investment decisions. This can indirectly influence firms' access to financing. In a slightly different context, Lin (2011) demonstrates that profitable firms are likely to rely more on long-term investment debt rather than bank loans, particularly when foreign banks enter the market.

The second stream of literature recalls behavioral aspects of financing decisions, i.e. expectations, perceptions and experience. Here, the perceived and actual financing needs are found to be key determinants in firms' decisions to inform themselves about external financing availability (Fidrmuc et al., 2024; Moscarini, 2004), build perceptions about financing options (Horky, 2024) and actively seek external financing (Danielson & Scott, 2004; De Haan & Hinloopen, 2003). Managers of SMEs must consider the costs and benefits associated with acquiring, updating, and processing new information about the external financing environment. This can lead to rational inattention, where new information is disregarded until it becomes important to the firm's immediate needs (Sims, 2003). Indeed, Fidrmuc et al. (2024) suggest that firms actively seek out and prepare relevant information only when the need for a loan arises, indicating a strategic approach to bank negotiations. Rational inattention can become a problem in an environment of limited financial literacy among SME managers, which can hinder their ability to understand complex financial products and bank terms (Moro et al., 2015). However, it is not just the general need for funds that is influential, but the specific nature of that need. Dell'Ariccia et al. (2012) demonstrate that for private households, refinancing loans are rejected more frequently than new or investment loans due to presumably poorer risk profiles. Given that many SMEs are driven by owner-managers, this finding may be applicable for their business loan application decisions too. In this vein, Drexler et al. (2014) note that for microenterprises,[3] the line between business and personal financial decisions is frequently unclear. This is particularly relevant in the context of financial decision-making, where biases such as optimism and pessimism can significantly sway judgments (Roger et al., 2018). In fact, De

[3] We refer to the Eurostat definitions of SMEs: The firm is a microenterprise if it has below 10 full-time employees, it is small if it has 49 or less full-time employees, the firm is medium sized if it has between 50 to 249 full-time employees or large if it has more than 250 full-time employees.

Meza and Southey (1996) nicely show that especially aspiring entrepreneurs are systematically over optimistic in evaluating their prospects and thus regularly denied when applying for credit. Given these tendencies, it is reasonable to infer that behavioral beliefs and expectations are influential when SMEs approach financing applications (Bianchi et al., 2022). Further empirical studies reinforce this conclusion. Massenot and Pettinicchi (2018) find that German firms exhibit an over-optimistic outlook on their future business situation following an improvement in business, while Barrero (2022) observes a tendency toward over-pessimism among U.S. firms experiencing a downturn. These behavioral biases also manifest themselves in firms' credit market beliefs (Fidrmuc et al., 2024) and external financing application behaviors (Horky & Fidrmuc, 2023). Aristei & Angori (2022) highlight strong state dependence in SMEs' access to bank credit. Past credit restrictions substantially reduce the likelihood of future successful loan applications. A more recent contribution by Fraser and Nguyen (2025) develops a dynamic Bayesian-learning model to explain discouraged borrowing. They show that firms update their expectations about loan approval based on past experiences, but that learning is inefficient. Discouraged borrowers exhibit similar ex-ante approval probabilities as applicants. This suggests that cognitive biases and imperfect learning processes, rather than objective credit risk, can increase discouragement and reduce overall credit-market efficiency.

Finally, the third stream of literature focusses on the supply side. The literature on credit supply and corporate financing is extensive, covering e.g. firm innovation (Amore et al., 2013), cyclical behaviors and credit supply shocks (Becker & Ivashina, 2014; Degryse et al., 2019; Alfaro et al., 2021), the role of loan guarantees (Bachas et al., 2021), the effects of banking regulation on credit supply (Hyun & Rhee, 2011). Our paper focusses on the firms' decision-making based on available information. Bernanke (2020) highlights that quantitative easing increases the supply of, and access to safe and liquid assets. Although it might be costly for SMEs' managers to form and retain an informed belief about the supply of bank finance, there is evidence that firms do attempt to stay informed about financial conditions. Berger & Udell (2006) indicate that SMEs adjust their financial strategies based on perceived credit availability, suggesting that information about the supply side of bank finance indeed impacts SME loan applications. Recent policy work from Dimou et al. (2025) highlights that banks' assessment of their credit standards as captured in the Bank Lending Survey (BLS) is closely related with firms' perceptions about the availability of bank loans as reported in the SAFE, supporting the aforementioned research results. We can further draw conclusions from the behavior of households, where we find evidence, that households use official statistics to form inflation expectations (Cavallo et al., 2017). Furthermore, Carrol (2003) shows that households form their beliefs on information taken from the news and professional forecastersc, which in turn are significantly influenced by information transmitted from authorities including central banks (Mitchell & Pearce, 2020).

Closest to our study are Kon & Storey (2003), Anastasiou, et al. (2022), and Ferrando & Mulier (2022). Kon & Storey (2003) provide the seminal theoretical foundation for the concept of discouraged borrowers. They model the loan application decision as a rational trade-off in which firms compare the expected benefits of applying against the expected costs, including the probability of rejection and the associated application costs. Their framework formalizes why firms may choose not to apply although they would likely qualify for a loan (self-exclusion). Anastasiou et al. (2022) complement this view by documenting how economic sentiment and volatility shape borrower discouragement across Euro area SMEs. Their results highlight that discouragement is also cyclical, being strongly linked to macroeconomic expectations. This is an important insight considering recent economic and geopolitical turbulences and the recent high interest-rate period. Even closer to our study is the one conducted by Ferrando & Mulier (2022) who investigate specifically discouraged firms and are also using the SAFE surveys. They provide evidence that firms in need of external finance trade off the costs and benefits of applying for a loan, given their expected rejection likelihood. They also hint at the inefficiency of this self-constraining behavior as 40% of discouraged firms would likely be able to obtain a loan. In addition, Cowling & Sclip (2023) explore the intertemporal dynamics of discouragement, showing that transitions into and out of discouragement depend on business cycle conditions, past credit experiences, and firm-specific risk factors. Improvements in profitability and credit history significantly reduce discouragement over time.

While the literature on bank loan application decisions is extensive, three central gaps remain where our analysis contributes to a better understanding. First, existing work typically treats non-application as a residual state, often collapsing it into a single category or ignoring it altogether. By contrast, our approach distinguishes between three forms of non-application, reliance on internal funds, discouragement, and other non-disclosed reasons and the application for a bank loan. This richer classification allows us to disentangle economically neutral behavior (availability of sufficient internal funds) from potentially inefficient self-exclusion (discouragement, other reasons). More specifically, we extend the empirical study of Ferrando & Mulier (2022) and the theoretical baseline by Kon & Storey (2003) by investigating firms' cost and benefit trade off across several outcomes. Second, prior studies emphasize either observable application outcomes or broad correlates of discouragement but rarely link them to a unifying theoretical framework. Building on Hackbarth et al. (2007) and Kon & Storey (2003), we interpret application and non-application decisions within a semi-structured expected-utility perspective that accounts for firm fundamentals, behavioral factors and the supply side. This provides a systematic way to evaluate how perceptions, beliefs, and informational frictions translate into financing choices. Third, while financing behavior is well known to vary with macroeconomic conditions, the unique sequence of shocks in our sample, the pre-COVID expansion, the COVID crisis, and the subsequent period of high interest rates, offers an opportunity to assess which determinants of (non-) application remain persistent and which adjust across regimes.

As a core novelty we propose an investigation framework following a structured decision process where firms first rely on internal funds, then form beliefs about loan approval (belief-driven channel), and finally assess costs and terms (cost-driven channel) before applying for a loan. The belief-driven and the cost-driven channel are of special interest in our investigation. We show that the same observed outcome, SMEs not applying for bank loans, can signal financial strength, negative behavioral biases, rational inattention or unfavorable costs and terms. For policymakers, this distinction is crucial. Understanding these underlying mechanisms and their importance, is key for designing effective SME financing policies. The belief-driven channel reflects a degree of rational inattention and can be potentially inefficient as shown by Ferrando & Mulier (2022). The cost-driven channel is the one which can be influenced by policy makers and offers a potential lever for fostering innovation and economic growth. To conduct our empirical investigation, we use data from the Survey on the Access to Finance of Enterprises (SAFE), a collaborative survey by the European Commission and the European Central Bank, conducted since 2008. This semi-annual survey covers a wide range of micro, small, medium and large enterprises in the EU, making it a strong resource for understanding firms' financing conditions and perceptions (Martinez et al., 2022). The granularity of the SAFE data allows not only an investigation of the observed outcomes (loan application with approval, rejection, etc.), but also of the usually unobserved outcomes (enough internal funds, discouragement). We complement the SAFE data by information obtained from the BLS to further capture supply side aspects.

The remainder of the paper is structured as follows: In section 2 we present the data we use. In section 3 we outline our empirical strategy including the expected utility model and the subsequent empirical tests. In section 4 we show the modelled scenarios using our expected utility framework. Section 5 contains the empirical tests and results. Section 6 concludes.

2. Data

2.1. The Survey on Access to Finance of Enterprises and the Bank Lending Survey

Our primary data source is the Survey on the Access to Finance of Enterprises (SAFE), collected biannually by the ECB and the European Commission since 2008. SAFE is unique in providing harmonized cross-country microdata on financing needs, applications for financing sources, outcomes, and perceptions of European firms, with particular emphasis on SMEs[4]. SAFE is the only harmonized firm-level data source that captures

[4] Martinez et al. (2022) provide a detailed meta-analysis covering papers that use the SAFE survey in research. They identify 22 papers using the SAFE since the first wave in 2009 until 2019. Especially since the Covid pandemic, the SAFE is used for research more frequently.

non-application behavior for financing sources together with the stated reasons. This feature makes it uniquely suited to study discouragement and other forms of self-exclusion, which cannot be observed in credit registers or balance sheet data. We use microdata from waves 11–34 (H2 2014 to H1 2025). Waves prior are excluded due to major redesigns of key questions, and the shorter quarterly waves introduced in 2024 (31 and 33) are omitted to maintain consistency.

We limit our examination to the euro area, focusing on the 19 countries that had adopted the euro during the aforementioned time frame, yielding a dataset of in total 202,232 observations. While the dataset has a panel component, most firms are observed only once. Moreover, the survey is conducted on a semi-annual basis only in 12[5] out of these 19 countries. About 18% of firms appear in at least two consecutive waves, allowing us to exploit lagged information to address potential endogeneity. Our dependent variable of interest is firms' bank loan application behavior, derived from SAFE's question on whether a bank loan was needed and whether an application was made. We distinguish four mutually exclusive outcomes: Application, Discouragement, Internal Funds, and Other Reasons. Their distribution is shown in Table 1.

Table 1 Dependent variable – Bank Loan Application behavior, split by categories

Category	Count	Share (%)
BLApp	**241,519**	**100**
Application	41,330	17.11
Internal Funds	59,689	24.71
Other Reasons	31,882	13.22
Discouraged	7,816	3.24
NA	100,802	41.72

Note: This table reports the distribution of SMEs' bank loan application outcomes based on the ECB/EC Survey on the Access to Finance of Enterprises (SAFE), waves 11–34 (2014H2–2025H1). The sample includes euro-area firms from 19 countries that had adopted the euro during the full period. Shares are calculated among all replies. Application: The firm applied for a bank loan; Discouraged: The firm did not apply for a bank loan because it believes it will get rejected; Internal Funds: The firm did not apply because it has sufficient internal funds; Other Reasons: The firm did not apply but did not disclose any reasons. This category is taken as our baseline category. NA: No answer/not applicable or relevant.

Informed by the literature, our primary explanatory variables encompass firm-fixed characteristics such as size (number of full-time employees), age (years of operation), and the primary sector of activity (Andrieu et al., 2018). We also consider whether the company required a bank loan for investment purposes or for refinancing (Fidrmuc et al., 2023; Sims, 2003). To mitigate possible endogeneity issues, we exploit the panel component of SAFE and include lagged indicators for past financial performance, measured by whether the firm increased its profits in the previous period (Orgler, 1970). Supply-side conditions are captured by our Bank Lending Survey index (Dell'Ariccia et al., 2012; Leary, 2009). Finally, we account for behavioral aspects, including firms' perception of current loan availability, their outlook for future credit availability, and their past experience with loan applications (Bianchi et al., 2022; Fidrmuc & Horky, 2023; Fidrmuc et al., 2024).

To capture supply-side conditions, we complement SAFE with the ECB's Bank Lending Survey (BLS). Specifically, we construct an index combining five dimensions of reported credit standards (impact of economic activity, firm/industry situation, liquidity, access to market finance, and banks' risk tolerance). The index is aggregated at the country–time level. Table 2 contains some descriptive overview of the independent variables, while we display the relevant questions from SAFE and possible answers in table A1 in the appendix. The correlation of the variables can be found in table A2 in the appendix.

[5] A list of these countries and an overview on whether they occur annually or semi-annual can be found in the appendix in table A3.

Table 2 Independent variables

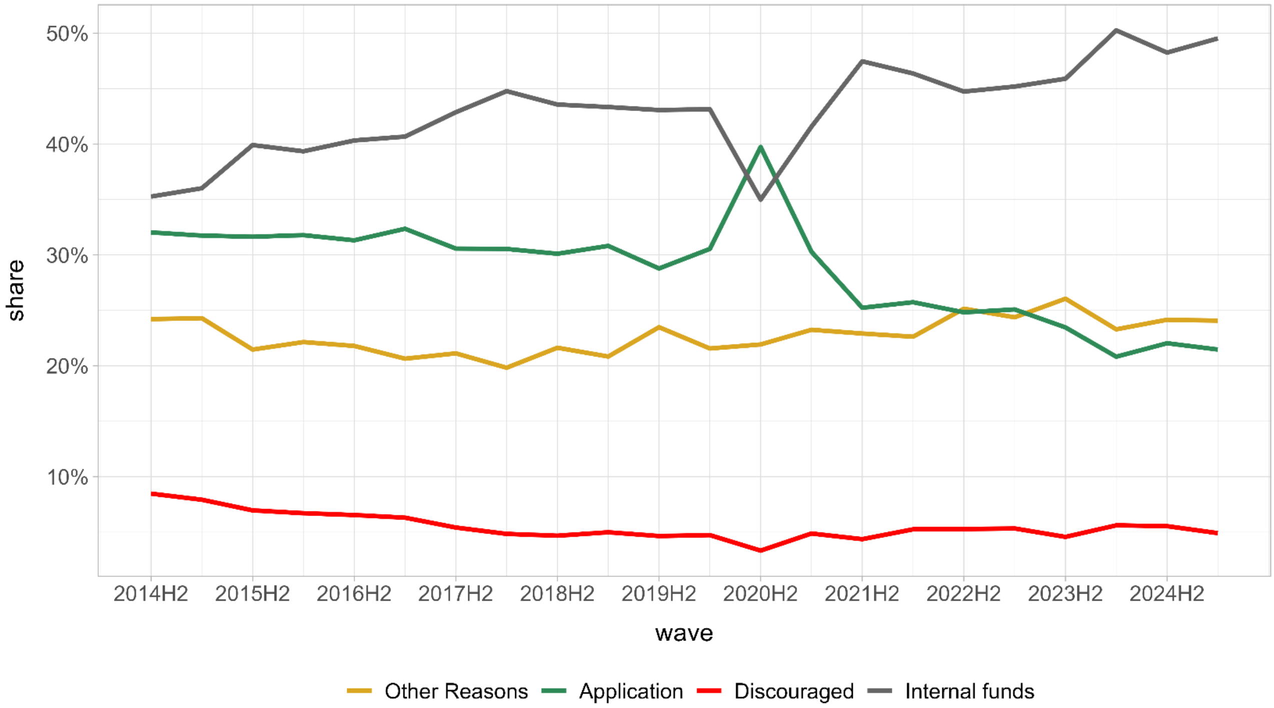
Variable	N	Mean	Std. Dev.	Min	Max
Lagged Other Reasons	42,765	0.212	0.407	0	1
Lagged Internal Funds	42,765	0.441	0.496	0	1
Lagged Discouraged	42,765	0.054	0.226	0	1
Lagged No Money	42,765	0.022	0.149	0	1
Lagged Received Everything	42,765	0.231	0.421	0	1
Lagged Received Parts	42,765	0.040	0.196	0	1
Size	241,282	–0.580	0.473	–1	1
Age	241,519	0.830	0.646	–1	1
BLS Index	241,519	0.062	0.251	–0.80	1.77
Lagged Profits	66,692	0.306	0.460	0	1
Investment	205,035	0.434	0.495	0	1
Refinancing	204,594	0.152	0.359	0	1
Lagged Bank Loan Perception	16,604	0.228	0.900	–1	1
Lagged Bank Loan Outlook	18,193	0.049	0.970	–1	1

Note: Variables derived from firms' past experiences with loan applications include No Money, Received Everything, and Received Parts. These indicate, respectively, that the firm was rejected (or refused the offered terms), received the full loan amount, or obtained only part of the requested loan.
Several explanatory variables (size, age, perception, outlook) are conceptually categorical in SAFE but are treated as continuous in our baseline specification. The rationale is that the underlying processes—firm growth in employees, firm aging, or shifts in credit perceptions—are inherently continuous. A continuous treatment allows us to capture monotonic marginal effects and to interpret estimated coefficients as reflecting directional changes across ordered groups.
We code these variables symmetrically around zero (–1, 0, 1) rather than using unbalanced scales (e.g., 0–2 or 1–3). This approach ensures comparability across variables, facilitates interpretation of zero as the "middle" or reference category, and avoids imposing artificial asymmetries in the estimation. In robustness checks, we also experimented with categorical dummies and alternative codings; results remain qualitatively unchanged.
The BLS index is a standardized composite measure of five lending condition dimensions reported by banks, aggregated at the country–time level. Values above zero indicate a net tightening of credit standards, while negative values denote easing.

2.2. Stylized Facts

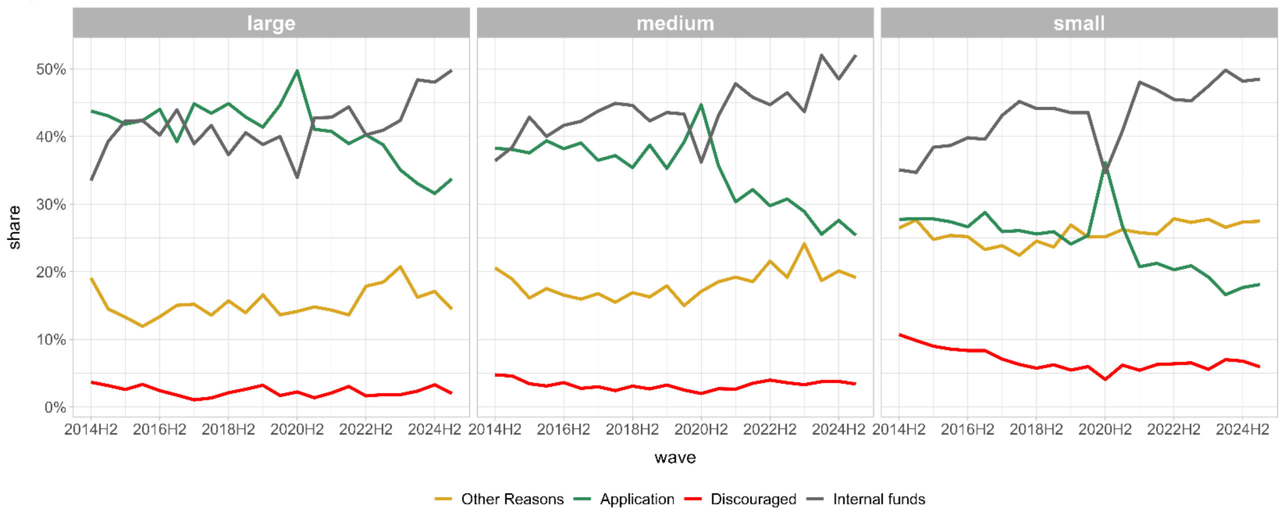
The main focus of our analysis is to disentangle the factors influencing a firm's decision-making process regarding bank loan applications. An analysis of the raw data depicting firms' application trends reveals several notable patterns. Figure 1 shows a decade-long decline in the share of firms actively applying for bank loans. The clear exception is the first COVID wave, when applications spiked—consistent with acute liquidity needs and government support schemes. Since then, application shares have fallen to about 20%, while reliance on internal funds has risen to roughly 50% recently. Around a quarter of firms report "other reasons" for non-application, with a rising trend in recent years. Around 5% of firms report discouragement. These patterns suggest a shift toward self-financing and a non-trivial degree of self-exclusion from the credit market, raising concerns about under-investment in a period of weak growth, high inflation, and elevated borrowing costs.

Figure 1 Bank Loan Application behavior over time



Note: ECB SAFE microdata, waves 11–34 (2014H1–2025H1), euro-area firms from19 countries that had adopted the euro during the whole period under investigation, quarterly short waves (31, 33) excluded. Shares are computed among firms with non-missing Bank loan application responses; categories sum to 100% in each wave. Application (applied for a bank loan), Discouraged (did not apply due to expected rejection), Internal Funds (did not apply because internal funds were sufficient), Other Reasons (did not apply; reason not specified).

Figure 2 Bank Loan Application behavior over time by firm size

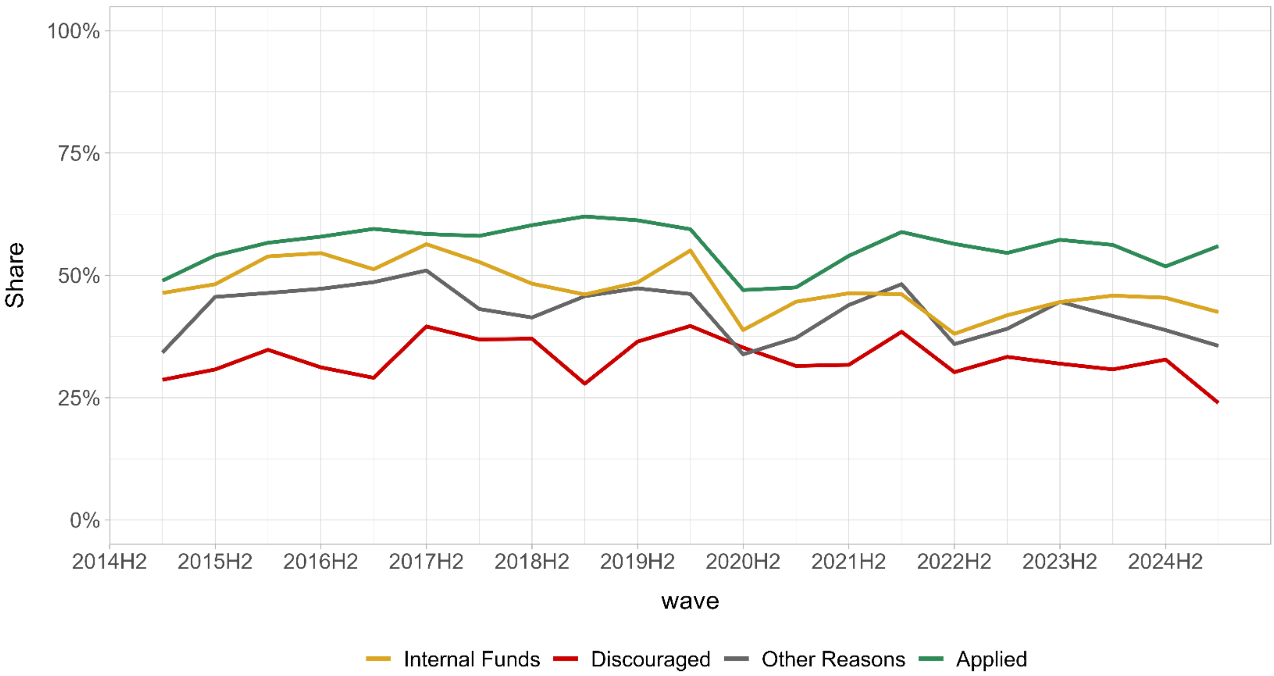


Note: Shares are calculated within each size group per wave, categories sum to 100% within group. Small < 50 FTE, Medium 50–249 FTE, Large ≥ 250 FTE (SAFE classification). The data covers SAFE waves 11–34 (2014H2–2025H1).

Disaggregating by firm size (Figure 2) shows marked heterogeneity. Overall, the share of bank loan applications declines by firm size. Regarding the recent economic environment, large firms maintained relatively stable application shares pre-COVID, with a decline in the last years. Medium-sized and small firms behave more sensitive displaying a sharp COVID-era spike followed by a pronounced post-pandemic decline. Non-application is also systematically higher for small firms: the shares of Other Reasons (≈25% in recent waves) and Discouraged (around 5–7%) are both above the levels observed for medium and large firms. In fact, fewer than one in five small firms apply for a bank loan in recent waves, making “Application” only the third most common outcome after Internal Funds and Other Reasons. This pattern strongly motivates our focus on investigating non-application behavior. Regarding firm age, younger firms generally report lower levels of bank loan application than older firms, which is in line with the literature. Still, the differences seem less pronounced than the ones observable across firm sizes (Figure A1). Finally, the sectoral analysis does not reveal strong deviations across sectors (Figure A2). The only notable difference occurs during the first wave of the COVID-19 pandemic, when only the construction sector did not experience a spike in bank loan applications.

Figure 3 illustrates that firms that previously applied for a bank loan display markedly higher investment activity than those that refrained from applying. On average, more than half of the firms that applied report investments in property, plants or equipment in the following period, compared with only around one quarter among discouraged firms and those abstaining for other reasons. Firms relying on internal funds fall in between, with investment rates of roughly 45–50%. These patterns indicate that active engagement with the credit market is closely associated with higher real investment, whereas discouragement and other forms of non-application coincide with less investment activity. This gap highlights the real-economic importance of self-exclusion from the credit market. Non-application behavior does not merely reflect sentiment or expectations but translates into lower firm-level investment and, by extension, weaker aggregate growth dynamics. From a macroeconomic perspective, this divergence in investment behavior implies that a non-negligible share of productive capacity remains underutilized because viable firms fail to obtain or even seek external financing. As discouraged firms often possess investment opportunities similar to successful applicants (Ferrando & Mulier, 2022), their withdrawal from the loan market effectively reduces the efficiency of capital allocation within the economy. The resulting investment gap can dampen productivity growth. In periods of tightening credit conditions, the prevalence of discouragement may therefore amplify cyclical slowdowns by constraining credit demand precisely when policy seeks to stimulate investment.

Figure 3 Investment behavior by previous bank loan application behavior

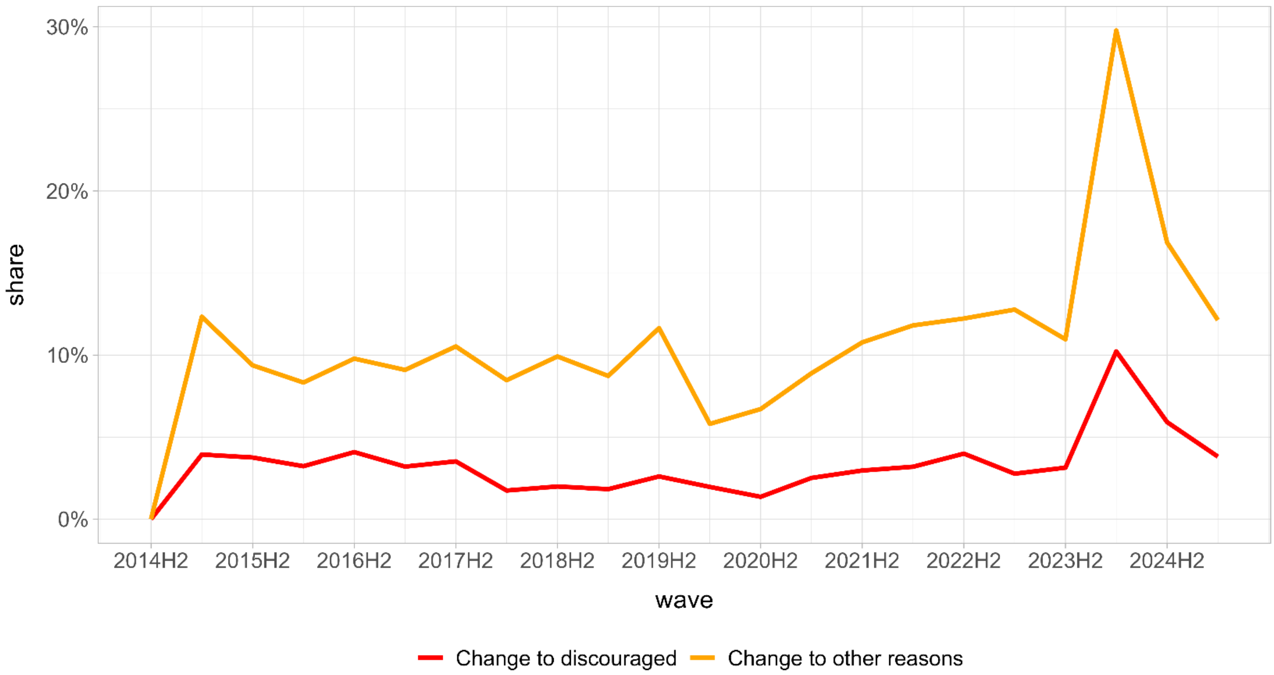


Notes: ECB SAFE microdata, waves 11–34 (2014H1–2025H1), euro-area firms from 12 countries that had adopted the euro throughout the sample period and have a semi-annual survey frequency. The figure shows the share of firms reporting investment into property, plants or equipment conditional on their previous bank loan application behavior: Applied, Discouraged, Internal Funds, and Other Reasons.

Figure 4 tracks flows from Application into negative non-application states, i.e. Discouraged or Other Reasons. Conditional on having applied in the previous wave, the share of firms switching to either Discouraged or Other Reasons remains fairly stable pre-pandemic, but jumps markedly in 2024H1–H2, peaking near 30% of the application base. This surge coincides with a period of tighter monetary conditions and heightened macro-uncertainty. Conceptually, these movements are consistent with Kon & Storey's (2003) model of discouraged borrowers: when expected rejection rises or application costs increase, otherwise viable firms may rationally choose not to apply. The pattern also dovetails with Ferrando & Mulier (2022), who show in SAFE that a sizable fraction of discouraged firms would likely have obtained a loan had they applied, implying potential inefficiency in the form of foregone investment. Our evidence suggests that such inefficiencies intensified during the recent tightening episode, with more prior applicants retreating from the market into non-application categories.

The striking increase in flows from application into Discouraged and Other Reasons in 2024H1–H2 likely reflects a combination of macro-financial forces. Sharp rises in borrowing costs and uncertainty about the rate path potentially increase perceived rejection risk and expected application costs. The withdrawal of pandemic-era support and tighter screening standards peaking in the end of 2023/the beginning of 2024 (Dimou et al., 2025) raise the hurdle for successful bank loan applications and heightened macro news and geopolitical shocks plausibly shift beliefs about the payoff from applying. Importantly, the shift from applying to non-application because of Other Reasons suggests latent financing needs that go unmet because firms step back from the market. These dynamics further justify why a disentangled view of non-application matters. Treating discouragement, other non-application, and internal funds as a single residual masks distinct mechanisms, beliefs about rejection, perceived application frictions, and genuine self-finance, that respond differently to shocks and carry different policy implications. To our knowledge, we are the first to separate these channels, explicitly discouragement and non-application due to non-disclosed reasons, and examine how shifts in the economic environment map into movements between them over time. This perspective turns non-application from an accounting residual into an object of analysis in its own right, and provides a clearer lens on when and why firms withdraw from the credit market even when external finance could be beneficial.

Figure 4 Change to non-application behavior



Note: This figure traces transitions from Application to non-application states, Discouraged or Other Reasons, between consecutive SAFE waves. The sample includes euro-area SMEs observed in at least two consecutive survey waves (waves 11–34, 2014H2–2025H1). Shares are computed among firms that had applied for a bank loan in t − 1. Discouraged denotes firms that abstain from applying because they expect rejection; Other Reasons refers to non-applicants without a stated reason.

3. Empirical Strategy

3.1. Modelling different bank loan application decision outcomes

Initially, we need to understand why a firm would choose between applying for a bank loan, using internal funds, or does not apply for a loan and forego an investment due to discouragement or other reasons. Therefore, similar as in Hackbarth et al. (2007), we assume that the SME can buy an EBIT generating machine, which is the only investment option available at investment cost I and generates a return *R(I)*. Unlike in Hackbarth et al. (2007) we specifically assume an SME which is not necessarily cash constrained, i.e. the firm has internal funds $F \in (0, I)$. Moreover, specific to SMEs, the firm can only issue external debt in a form of bank loan (bank debt) *B*, but no market debt (i.e. cannot issue securities), nor can it easily raise equity to cover investment costs. Let *B* denote the face value of bank debt if the application is approved. The firm receives net proceeds $(1-\phi)B$ at t=0, where $\phi \in (0,1)$ is a proportional flotation cost (fees/time costs), i.e. for every Euro raised, ϕ is paid out directly as fees or implicitly as time effort required to manage the loan. The funding condition when using bank debt therefore is:

$$I - F = (1-\phi)B \qquad \text{Eq. (1)}$$

At maturity, the firm must repay the full face value of *B* plus interest rate payments *r*. Now, we consider a firm operating in two periods, t=0 (decision) and t=1 (realization of wealth), with an initial firm value V_0. Let $S_s(\cdot)$ denote a multiplicative shock operator that maps V_0 into post-shock value $S_s(V_0)$, with $S_0(V_0) = V_0$ and $\frac{\partial S_s(V_0)}{\partial s} < 0$. We do not impose a functional form of the shock as the specific form is irrelevant for our empirical implementation. At t=0, the firm chooses among four financing strategies to fund, or not fund the EBIT generating machine:

$$\begin{Bmatrix} Application\ (A) \\ Internal\ Funds\ (I) \\ Discouraged\ (D) \\ Other\ Reasons\ (O) \end{Bmatrix}$$

Generally, our model follows the assumptions of Kon & Storey (2003). In case the firm applies for a bank loan, the final value of the firm can be written as follows if the loan gets approved:

$$V_1^{A,approved} = S_s(V_0) - F - C - (1+r)B + R(I), \qquad \text{Eq. (2)}$$

with

$$B = \frac{I-F}{(1-\phi)}, \qquad \text{Eq. (3)}$$

and *C* being upfront application costs[6]. Otherwise, if the loan is not approved the final value is:

$$V_1^{A,denied} = S_s(V_0) - C \qquad \text{Eq. (4)}$$

Hence, the expected final value in case the firm applies is:

$$E(V_1^A) = pV_1^{A,approved} + (1-p)V_1^{A,denied} \qquad \text{Eq. (5)}$$

Here $p \in (0,1)$ denotes the firm's subjective approval belief at t=0, formed from its information set. In the spirit of Kon & Storey (2003), this belief, not the ex post bank decision, governs the application choice. In case *F* ≥ *I*, the firm could self-finance the EBIT generating machine, with the final value being:

[6] For example necessary legal advice and documentation, but also indirect time effort the (owner) managers have to spend for information acquisition which can not be used for productive work.

$$V_1^I = S_s(V_0) - I + R(I) \quad \text{Eq. (6)}$$

Finally, we distinguish two conceptually different forms of non-application. Discouraged (D) captures cases where the firm's subjective approval belief p is sufficiently low that applying is not worthwhile even before considering borrowing costs. Other Reasons (O) captures cases where p is not the binding constraint but the perceived costs of borrowing, i.e. application cost *C*, flotation cost ϕ, and interest rate *r*, make applying unattractive. In both D and O the firm does not invest in the EBIT generating machine in the current period, so the realized payoff is the status quo, but the latent drivers differ.

$$V_1^D = V_1^O = S_s(V_0) \quad \text{Eq. (7)}$$

As a standard assumption the firm tries to maximize its value in *t=1*:

$$\arg \max_{j \in (\mathrm{A,I,D,O})} V_1^j \quad \text{Eq. (8)}$$

Based on the defined application decision outcomes we can derive the following threshold conditions. Using Eqs. (2), (4), (5), and (7), the gain from applying relative to no investment, i.e. D and O, is:

$$E[V_1^A] - V_1^{D,O} = p[R(I) - F - (1+r)B] - C \quad \text{Eq. (9)}$$

Hence application beats the status quo, under *p** as belief threshold, if:

$$p \geq p^* \equiv \frac{C}{R(I) - F - (1+r)B}, \text{and } R(I) - F - (1+r)B > 0 \quad \text{Eq. (10)}$$

When $R(I) - F - (1+r)B \leq 0$ or $p^* > 1$, applying is never attractive relative to no investment, even with optimistic beliefs (*p=1*). Comparing Application to Internal Funds (Eq. (6)) yields:

$$E[V_1^A] - V_1^I = p[R(I) - F - (1+r)B] - C - (R(I) - I), \quad \text{Eq. (11)}$$

so, application beats self-finance if:

$$p \geq p^* \equiv \frac{C + (R(I) - I)}{R(I) - F - (1+r)B}, \text{and } R(I) - F - (1+r)B > 0 \quad \text{Eq. (12)}$$

Therefore, a higher project NPV under self-finance $(R(I) - I)$ raises p^* making a bank loan application harder to justify. Mapping the threshold conditions specifically to non-application decisions we observe the following results. For discouraged firms $p < p^*$ while the terms would justify applying at high beliefs $(R(I) - F - (1+r)B > 0)$, thus discouragement is believe-driven. Firms not applying for other reasons face $R(I) - F - (1+r)B \leq C$, or $p^* > 1$ equivalently, meaning that even at *p=1* applying for a bank loan does not beat the status quo. This form of non-application is therefore cost-driven. Internal funds is chosen under the condition of sufficient *F* and when self-finance dominates given *p* and *C*, ϕ and *r*. Although the framework formalizes the firm's decision as a simultaneous comparison across all financing alternatives, the underlying cognitive process can be viewed as stepwise. In practice, SMEs likely follow a sequential evaluation: (i) assess whether investment is desired and internal funds suffice, (ii) form beliefs about loan approval conditional on an application (belief-driven channel), and (iii) evaluate the expected costs and terms of borrowing (cost-driven channel). Only if this last step yields a positive net benefit the firm applies. The simultaneous representation in the expected-utility framework simply collapses this stepwise reasoning into a single optimization problem, since all alternatives are mentally accessible and compared within the firm's decision set, and only one outcome can be realized at one point in time. Hence, the structural thresholds derived can be interpreted as the reduced-form results of this sequential evaluation.

3.2. An expected utility framework for bank loan application decisions

The payoff expressions in Eqs. (2) to (7) imply that choice probabilities depend on primitives $\{p, C, \phi, r, F, R(I)\}$. These are only partially observable in reality and can only be proxied qualitatively with SAFE and BLS items.

The choice among {A, I, D, O} can be captured by a general expected-utility style index with subjective beliefs based on the period-1 payoffs in Eqs. (2) to (7). We assume only that each option admits a risk-adjusted payoff index $m_j(x)$ (e.g., a certainty equivalent) that is strictly increasing in the underlying payoff $V_1^j(x)$. Thus, only the ordinal ranking of alternatives matters and any strictly increasing reparameterization leaves choices unchanged. We therefore represent each alternative *j* by a latent utility:

$$U_j(x) = \alpha_j + \beta m_j(x) + \eta_j \qquad \text{Eq. (13)}$$

where η_j captures unobserved tastes and information. This formulation allows to keep the mapping to structural payoffs. Crucially, Discouraged (D) and Other reasons (O) can yield the same pecuniary payoff in the current period yet differ in utility through their mechanism components, i.e. a belief-driven avoidance for D versus cost -driven avoidance for O, consistent with the threshold conditions in Section 3.1. Guided by this, we specify the risk-adjusted payoff indices for the four outcomes as:

$$m_A(x) = p(x)\big[R(I,x) - F(x) - \big(1 + r(x)\big)B(x)\big] - C(x) \qquad \text{Eq. (14)}$$

$$m_I(x) = R(I,x) - I, \qquad with\; F(x) \geq I \qquad \text{Eq. (15)}$$

$$m_D(x) = 0 + \psi_D(1 - p(x)) \qquad \text{Eq. (16)}$$

$$m_O(x) = 0 + \psi_O(C(x), \phi(\mathrm{x}), r(\mathrm{x})) \qquad \text{Eq. (17)}$$

The terms $\psi_D(\cdot)$ and $\psi_O(\cdot)$ capture the non-pecuniary mechanism components that differentiate belief-driven discouragement from cost-driven non-application even when the pecuniary part equals. This formulation accommodates risk attitudes and non-pecuniary components while keeping the mapping to structural payoffs.

To keep the link between data and mechanisms transparent, we adopt a direct, nonparametric mapping from observables to the primitives in Eqs. (14) – (17): (i) Costs $(C,\ r,\ \phi)$ are proxied as functions of size, age, and BLS. We assume larger/older firms plausibly face lower application and frictional costs combined with better terms, while tighter BLS raises all three via screening intensity, pricing, and non-price conditions. (ii) Own funds F are a function of increased lagged profits as this gives us a qualitative indication of internal liquidity. (iii) The project payoff $R(I)$ can be proxied by the reasons for needing external financing. I.e. if external financing is required for investment purposes, this raises the incremental return, while refinancing need potentially lowers the incremental return of new borrowing. (iv) The approval belief *p* depends on past availability perception and future availability outlook reported by the firm. Formally, we can write:

$$\begin{gathered}
\big(C, \phi, r(\mathrm{x})\big) \rightarrow h_c(size, age, BLS) \\
R(I,x) \rightarrow h_R(Investment, Refinancing) \\
F(x) \rightarrow h_F(lagged\ Profit) \\
p(x) \rightarrow h_p(lagged\ Perception, lagged\ Outlook)
\end{gathered} \qquad \text{Eqs. (18)}$$

with $h(\cdot)$ left unspecified and monotone in the economically natural directions. Substituting these primitives into Eqs. (14) to (17) delivers $m_j(x)$ and thus the latent utilities in Eq. (13). This specification ensures that all four utilities are determined jointly from the same information set. Given the direct mappings we approximate each unknown $h(\cdot)$ by its first-order linear projection on observables. Substituting this into the payoff indices in Eqs. (14) – (17) yields the following index representation:

$$m_j(x) \to \theta_j^T x \ = \sum_{k=1}^{K} \theta_{j,k} x_k \qquad \text{Eq. (19)}$$

Where $\theta_j = (\theta_{j1}, \dots, \theta_{jk})$ are outcome specific calibrated parameters for the respective observables x_k. Hence, the systematic part of the laten utility (Eq. 13) for each outcome is a linear combination of the relevant observables.

To operationalize the index representation in Eq. (19) for our subsequent scenario modelling, we proceed in three steps. First, for each outcome $j \in \{A, I, D, O\}$ we estimate a linear model on the full, common set of observables *x*:

$$y_{j,c} = \alpha_j + \sum_{k=1}^{K} \beta_{j,k} x_{k,c} + \varepsilon_{j,c} \qquad \text{Eq. (20)}$$

where $y_{j,c}$ is the indicator for outcome *j* of firm *c*. Second, from each modelled outcome *j*, we extract the direction $s_{j,k} = sign(\beta_{j,k})$ and the relative importance[7] $\omega_{j,k}$ of each covariate *k* using the Lindeman-Merenda-Gold (LMG) decomposition[8] as defined by Lindemann et al. (1980) and refined in Grömping (2007). Third, for the calibration of Eq. 19 we retain signs and weights obtained from Eq. 20 only for the mapped variables defined in Eqs. (18)[9]. We pass the resulting linear combination of relevant observables through a probit link, where $\Phi(\cdot)$ denotes the standard normal CDF, and then normalize across alternatives:

$$\pi_j = \frac{\Phi\left(\sum_{k=1}^{K} s_{j,k}\, \omega_{j,k} x_k\right)}{\sum_{j \in \{A,I,D,O\}} \Phi\left(\sum_{k=1}^{K} s_{j,k}\, \omega_{j,k} x_k\right)} \qquad \text{Eq. (21)}$$

Because $\Phi(\cdot)$ is strictly increasing and the index is linear in *x*, this transformation preserves the ordinal ranking of outcomes and allows us to use the vector π for visualization and comparative evaluation of the potential choice.

We do not claim full structural identification of primitives. The mapping from proxies to primitives is approximate and many-to-one. Our goal is directional identification: Monotone effects of belief proxies on Discouraged vs. Application, monotone effects of cost/term proxies on Application vs. Other Reasons and monotone effects of lagged profits on Internal Funds vs. Application. We encode these as sign and ordering restrictions based on the relative importance and sing extraction. We test their empirical validity in the Multinomial Logit Model described in the following section. This interpretation is consistent with the notion of rational inattention (Sims 2003; Matejka & McKay 2015). Discrete-choice probabilities can emerge from an agent's optimal but limited information processing capacity. SMEs in our setting decide how much attention to allocate to learning about

---

[7] We prefer relative-importance weights over raw coefficients (or marginal effects) for three reasons. First, comparability: coefficient magnitudes in separate outcome models are scale-dependent, whereas LMG apportions the share of explained variation (R^2) attributable to each regressor and is thus unit-free and comparable across outcomes. Moreover, our calibration needs direction (sign) and influence (weight) to build single-index utilities and visualize comparative statics. LMG delivers exactly this, a set of robust, model-consistent weights without imposing a structural probability interpretation that marginal effects would suggest. It holds:

$$\sum_{k=1}^{K} \omega_{j,k} = 1, \text{and } \omega_{j,k} > 0$$

[8] We measure each regressor's contribution using the Lindeman-Merenda-Gold (LMG) decomposition, implemented via the R package relimpo. LMG defines a variable's importance as its average incremental R^2 over all possible regressor orderings. In linear models this coincides with the Shapley value allocation of the model R^2 from cooperative game theory (see for instance: see Lindeman et al., 1980, Kruskal (1987) and Grömping, 2007). Hence our reported LMG weights are Shapley value consistent measures of relative importance in the linear models used for calibration.

[9] We estimate each outcome model on the full covariate set to have stable LMG weights on a full informational set. This ensures that the signs and importances for the mapped variables are computed conditional on same controls.

external credit conditions. Belief-driven discouragement thus arises naturally as an outcome of selective information acquisition.

3.3. (Multinomial) Logit Models for Bank Loan Application Behavior

In the econometric exercise we aim to substantiate the theoretical underpinnings of our model with robust statistical evidence. Relative importance, as captured by our LMG decomposition, provides insight into the contribution of each predictor to the model's predictive power, while statistical significance offers a measure of the confidence. The bank loan application decision presents a categorical target variable with unknown ordering. In such a scenario of multiple, discrete decision alternatives, the multinomial logit model is feasible, especially in the case of loan decisions, where no strong justification of underlying normality of the outcomes can be made (Lawrence & Arshadi, 1995). Let y_{ct} denote the choice made by firm *c*, which can be one of *J* possible outcomes. The probability that firm *c* chooses option *j* is then modeled as:

$$P(y_c = j|Z_c) = \frac{e^{\beta_k Z_c}}{\sum_{k=1}^{K} e^{\beta_k Z_c}} \qquad \text{Eq. (22)}$$

Here, Z_{ct} is a vector of variables for firm *c*, and β_k represents the parameters to be estimated for each variable *k* in respect to the choice *j*. The denominator ensures that the probabilities across all choices sum to one. The vector of variables has the following form:

$$\beta_k Z_c = \boldsymbol{\beta} \boldsymbol{X}_c + \sum_{k}^{K} \delta_k exp_{ct-1} + \boldsymbol{\theta} + \varepsilon_{ct} \qquad \text{Eq. (23)}$$

where $\boldsymbol{X}_c$ is the vector of variables we already use in the modelling approach, $\boldsymbol{\theta}$ is a set of fixed-effects, specifically year, country and sector effects. We complement this by $\sum_k^K \delta_k exp_{ct-1}$, which denotes the former experience the firm had with bank loan applications.

Finally, we investigate state transitions to discouragement or non-application due to other reasons. For this purpose, we define $y_{ct}^{j \to l}$ as a binary variable that equals 1 if firm *c* transitions to being discouraged at time *t* (conditional on not being discouraged in *t−1*) and 0 otherwise. The logit model is then specified as:

$$\log\left(\frac{P(y_{ct}^{j \to l} = 1|\boldsymbol{Z}_{ct})}{1 - P(y_{ct}^{j \to l} = 1|\boldsymbol{Z}_{ct})}\right) = \alpha + \boldsymbol{\beta} \boldsymbol{X}_{ct} + \sum_{k}^{K} \delta_k exp_{ct-1} + \boldsymbol{\theta} + \varepsilon_{ct} \qquad \text{Eq. (24)}$$

where the set of variables is similar to the specifications above. In the second exercise we define $y_{ct}^{j \to l}$ as a binary variable that equals 1 if firm *c* transitions to not applying due to other reasons at time *t* (conditional on not applying due to other reasons in *t−1*) and 0 otherwise.

Working with survey data such as the SAFE dataset always presents inherent challenges that cannot be overlooked, notably self-selection and self-reporting biases. These biases may lead to systematic differences between participating firms and those that do not respond—particularly as companies in financial distress or already discouraged might be less inclined to participate. However, the institutional survey background provided by the ECB ensures the application of state-of-the-art sampling methods and rigorous survey conduction standards.

4. Expected Utility Scenario Modelling

Building on the index representation in Eq. (19), we first estimate Eq. (20) for each outcome $j \in \{A, I, D, O\}$ on the common set of observables *x*. From these fitted models we extract the sign $s_{j,k}$ and the LMG relative importance $\omega_{j,k}$. Using the primitive-observable mapping in Eqs. (18), we then retain only the mapped covariates for each outcome and construct the calibrated indices as linear combinations:

$$\widehat{m}_A(x) = \sum_{k \in K_A} \omega_{A,k}\, s_{A,k} x_k, \qquad \text{Eq. (25)}$$

$$K_A = \begin{Bmatrix} size, age, BLS, Investment, Refinancing, lagged\ Profits, \\ lagged\ Outlook, lagged\ Perception \end{Bmatrix}$$

$$\widehat{m}_I(x) = \sum_{k \in K_I} \omega_{I,k}\, s_{I,k} x_k, \qquad \text{Eq. (26)}$$

$$K_I = \{Investment, Refinancing, lagged\ Profits\}$$

$$\widehat{m}_D(x) = \sum_{k \in K_D} \omega_{D,k}\, s_{D,k} x_k, \qquad \text{Eq. (27)}$$

$$K_D = \{lagged\ Perception, lagged\ Outlook\}$$

$$\widehat{m}_O(x) = \sum_{k \in K_O} \omega_{O,k}\, s_{O,k} x_k, \qquad \text{Eq. (28)}$$

$$K_O = \{size, age, BLS\}$$

This keeps the link from mechanisms to data transparent (belief-driven *D*, cost/terms-driven *O*, own-funds *I*, full set for *A*) while ensuring all four outcomes are constructed on a common scale. The full linear models and complete LMG decompositions with all covariates are reported in Tables B1 and B2 in Appendix B. Table 3 reports the selected signs and weights for the mapped covariates.

Here, the weights line up cleanly with the mechanisms implied by the thresholds. For Application (A) the two largest contributors are investment need (+ 0.419) and size (+ 0.386), with tighter credit supply, BLS, dampening applications (- 0.113). Small but positive roles for bank loan availability perception and outlook are consistent with beliefs raising the net expected gain from applying. Discouragement (D) is overwhelmingly belief-driven, negative weights on perception (- 0.439) and outlook (- 0.179) together explain well over half of its index, exactly as the theoretical threshold models predict. By contrast, the mapped observables account for less than half of the index for Internal Funds (I) and Other Reasons (O) (≈0.28 and ≈0.38, respectively). This below-50% coverage for I and O reflects some limitations of our mapping rather than a modeling artifact. It has to be acknowledged that SAFE and BLS offer only qualitative answers, meaning that the answers are somewhat fuzzy proxies for the underlying primitives. Nevertheless, these surveys stays the best data source to substantiate our theoretical considerations. Even for the two categories with lower overall variable weight, the signs are uniformly as expected and the mapped observables still comparably important, when comparing to the other outcomes in Table B2 in the Appenidx or here to A, where all observables are included. This becomes clearly visible for the size effect on A compared to O (- 0.340), showcasing that smaller firms face higher costs and thus refrain from applying for a loan. Moreover, lagged Profits, although only containing a weight of (+ 0.116) for I, the weight is around 10 times higher than for A.

To connect the empirical indices in a first step to the theoretical threshold mechanisms, we consider the sign-importance structure in Table 3 along three salient channels: The belief driven channel (A vs D), the terms and costs driven channel (A vs O), and the liquidity channel (A vs I). On the belief margin, availability perception and outlook carry small positive weight for A (+ 0.017, + 0.023) but large negative weight for D (- 0.439, - 0.179), implying that improvements in beliefs enable reallocation from discouragement to application. On the terms and costs driven channel, size and age are increasing A (+ 0.386, + 0.019) but negatively affecting O (- 0.340, -0.020), while BLS enters negatively for A (- 0.113) and positively for O (+ 0.015), consistent with tighter supply pushing firms into non-application for other reasons. Finally, on the liquidity channel, lagged profits pull toward I (+ 0.116) and only weakly toward A (+ 0.015).

Table 3 Signs and Weights of the variables in the respective utility functions

	Application (A)		Internal Funds (I)		Discouraged (D)		Other Reasons (O)	
	Sign	Weight	Sign	Weight	Sign	Weight	Sign	Weight
Size	+	0.386					-	0.340
Age	+	0.019					-	0.020
Lagged Perception	+	0.017			-	0.439		
Lagged Outlook	+	0.023			-	0.179		
Lagged Profits	+	0.015	+	0.116				
Investment Need	+	0.419	-	0.062				
Refinancing Need	+	0.005	-	0.104				
BLS Index	-	0.113					+	0.015

Note: This table reports the direction and relative weight of key variables in the calibrated expected-utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, derived from the index representation in Equation (19). Signs reflect the estimated direction of each covariate, while weights correspond to LMG relative-importance values from the linear models described in Equation (20). SAFE microdata (waves 11–34) are combined with the ECB Bank Lending Survey (BLS) index to capture supply-side conditions.

Subsequently we use the calibrated payoff index representations to estimate several scenarios. We focus especially on potential scenarios creating non-application behavior due to discouragement or for other reasons. The firm size and the supply side as captured by the BLS serve as our increments, while the pre-COVID vs the post-COVID bank loan availability perception and outlook averages are our main scenario creating measures. All other variables are kept at sample mean in our modelling. An overview of the estimated scenarios can be found in Table 4.

We focus on scenarios 1,3,4 and 9, i.e. the role of firm size and supply levels, given certain bank loan availability perception and outlook levels[10]. Scenarios 1 and 4 cover the positive or optimistic pre-COVID levels of bank loan availability perception and outlook levels, while scenarios 3 and 9 cover the negative or pessimistic post-COVID bank loan availability perception and outlook levels. Scenarios 1 and 3 are depicted in Figure 5. For scenario 1, we observe, that as size rises, the utility index for Application increases while the utility for non-application due to Other reasons declines. Internal funds and Discouragement remain comparatively flat moving only mechanically through the normalization. The key qualitative feature is a rank switch around mid-small firms. Approximately at size ≈ -0.3 the ordering between not applying for Other reasons and Application reverses making a bank loan application the preferable outcome. Considering the sample mean of -0.580 for the firm size, this result suggests that the typical SME in our data is close to this point of indifference between applying and not applying for a bank loan. Small shifts that reduce effective borrowing frictions for such small firms can therefore flip the utility outcome from O to A for a large mass of firms. Symmetrically, modest adverse shocks potentially push a disproportionate number of firms into O. For scenario 3 we see, Other Reasons is the top-ranked option across the whole model, i.e. all supply levels. This is largely mechanical: the average firm in our data is small, and in our mapping small size raises effective borrowing frictions, pushing up O. Nevertheless, the utility index for Application provides an interesting direction. As expected, it substantially falls with higher BLS. With massive (theoretical) tightening, it collapses to being the least preferred behavior for (small) firms. Thus, confirming the potential influence of the supply side on bank loan application behavior.

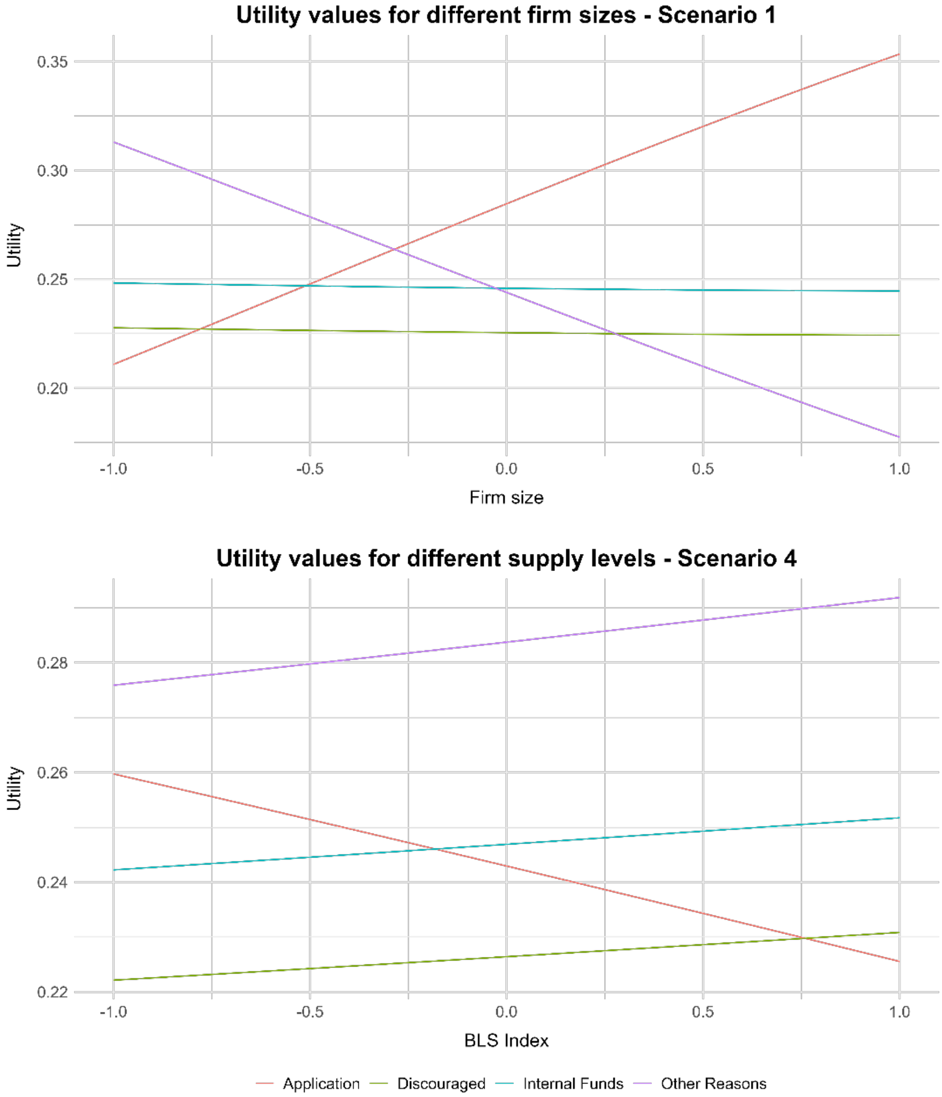
[10] The other scenarios for further robustness purposes can be found in Appendix B in Figures B1 to B5.

Table 4 Estimated scenarios

Scenario	Fixed variables	Modelled variation
1	Lagged Perception: 0.23 (sample mean) Lagged Outlook: 0.05 (sample mean) All other at sample mean	Firm size: -1 to 1 in 0.01 increments
2	Lagged Perception: 0 Lagged Outlook: 0 All other at sample mean	Firm size: -1 to 1 in 0.01 increments
3	Lagged Perception: -0.13 (mean for the last 6 waves, 2022H2 to 2025H1) Lagged Outlook: -0.349 (mean for the last 6 waves, 2022H2 to 2025H1) All other at sample mean	Firm size: -1 to 1 in 0.01 increments
4	Lagged Perception: 0.23 (sample mean) Lagged Outlook: 0.05 (sample mean) All other at sample mean	BLS Index: -1 to 1 in 0.01 increments
5	Lagged Perception: 0 Lagged Outlook: 0 All other at sample mean	BLS Index: -1 to 1 in 0.01 increments
6	Lagged Perception-0.13 (mean for the last 6 waves, 2022H2 to 2025H1) Lagged Outlook: -0.349 (mean for the last 6 waves, 2022H2 to 2025H1) All other at sample mean	BLS Index: -1 to 1 in 0.01 increments
7	Lagged Perception: 0.23 (sample mean) Lagged Outlook: 0.05 (sample mean) Firm size: 0 All other at sample mean	BLS Index: -1 to 1 in 0.01 increments
8	Lagged Perception: 0 Lagged Outlook: 0 Firm size: 0 All other at sample mean	BLS Index: -1 to 1 in 0.01 increments
9	Lagged Perception: -0.13 (mean for the last 6 waves, 2022H2 to 2025H1) Lagged Outlook: -0.349 (mean for the last 6 waves, 2022H2 to 2025H1) Firm size: 0 All other at sample mean	BLS Index: -1 to 1 in 0.01 increments

Note: This table summarizes the parameter settings used in the scenario simulations based on the calibrated utility-index functions (Equations 25–28). Each scenario varies either firm size or the BLS index across the range [−1, 1] in 0.01 increments while holding other variables at their sample means. Scenarios 1–3 vary firm size under alternative belief settings (pre-COVID, neutral, post-COVID), whereas Scenarios 4–9 vary credit-supply conditions. Lagged perception and outlook values are taken from SAFE waves corresponding to the pre-COVID (H2 2014–H2 2019) and post-COVID (H2 2022–H1 2025) periods.

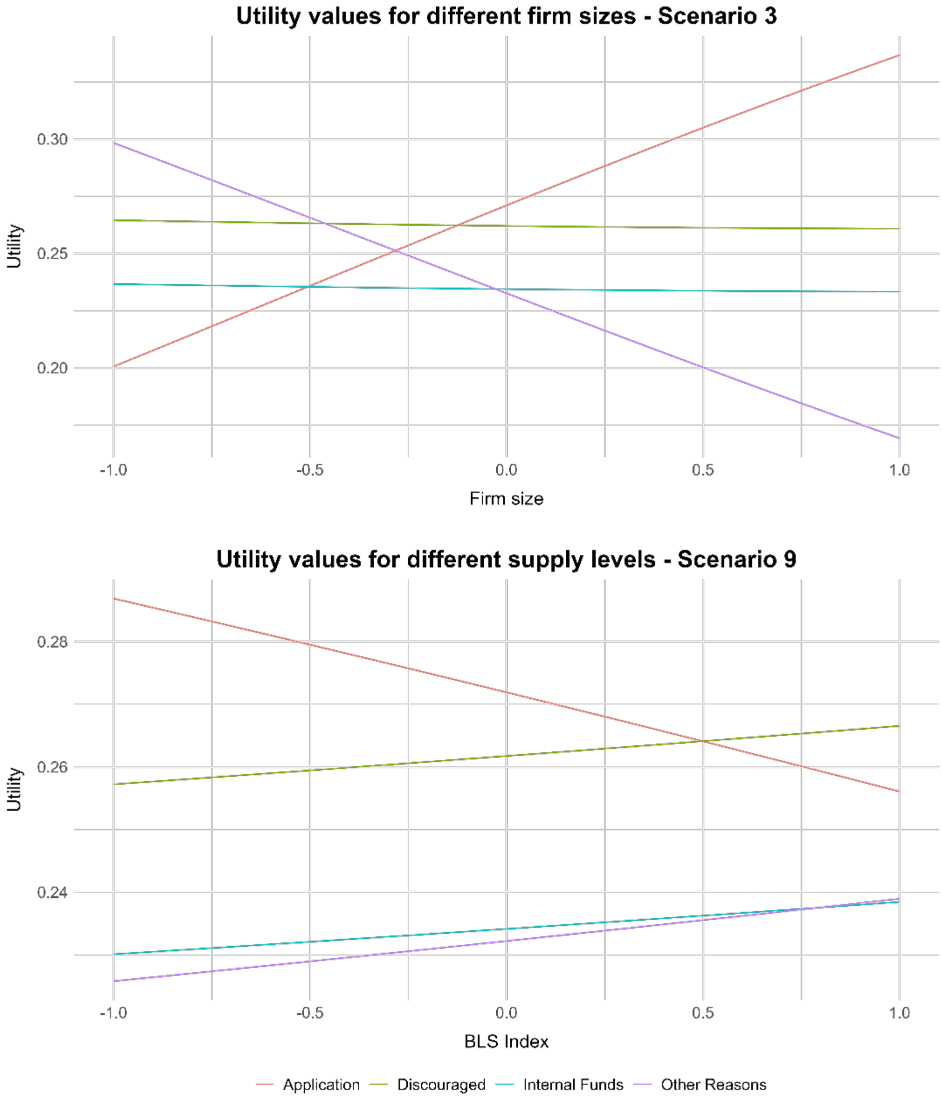
Figure 5 Scenarios with full sample bank loan availabilty beliefs for different firm sizes and supply levels (Scenarios 1 and 3)



Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under two scenarios. Scenario 1 assumes optimistic (pre-COVID) bank-loan-availability beliefs. Scenario 3 assumes pessimistic (post-COVID) beliefs. Firm size varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A Firm size of 0 denotes a medium-sized firm. Positive BLS Index values denote tighter lending standards.

Figure 6 contains scenarios 3 and 9 with (pessimistic) post Covid-COVID beliefs about bank loan availability. In scenario 3 we observe the ranking of preferred behavior switching twice as size increases. First, around size ≈ −0.5 we see a switch between "Other reasons" (O) and Discouraged (D), implying that even in the presence of negative beliefs for very small firms O is the preferred behavior. Between a firm size of≈ −0.5 and ≈ −0.2, discouragement becomes the behavior with the highest utility index. Beyond that point, the Application (A) index, which rises steeply with size, overtakes D and becomes the most attractive choice for larger SMEs. Internal funds (I) stays comparatively flat throughout, never dominating. Contrasting scenario 1 with scenario 3, i.e. positive pre-COVID with negative post-COVID bank loan-availability beliefs, two economically important shifts emerge. First, a new discouragement region opens up for small-to-mid-sized firms (≈ −0.5 to −0.2) in which not applying due to beliefs has the highest utility. Considering the sample mean of -0.580 for the firm size again, we see that a discouragement margin is well in reach for the average firm in the post-COVID environment. Second, the threshold at which a bank loan application becomes preferred moves substantially to the right, making A only preferred to even larger firms. Both shifts are unfavourable from a macro perspective. As shown by the literature, especially discouragement is often inefficient as many of these firms would receive a loan at acceptable terms. Second, concentrating non-application behavior not only around very small firms but also mid-sized SMEs potentially hampers recovery and causes weaker innovation diffusion after an economic shock like the COVID pandemic. As we observe this shifting behavior around medium-sized firms and additionally know that most small firms do not apply because of other reasons, i.e. the cost structure, we additionally focus on scenario 9, covering medium-sized firms with negative post COVID beliefs about bank loan availability and changing supply levels. In this scenario the calibrated indices show Application (A) as the top option when credit supply is loose or neutral. As the BLS index tightens the A index declines monotonically, while D remains essentially flat. The ranking flips at about BLS ≈ +0.5, where D overtakes A and becomes the preferred behaviour. “Internal Funds” and “Other Reasons” move only mildly with BLS and never dominate in this configuration. This switch at BLS ≈ +0.5 demonstrates a supply-driven discouragement margin under certain circumstances. In the post COVID sample (H2 2022 to H1 2025) the average BLS Index value was 0.197. Although this is well below the threshold in the scenario for medium-sized firms, it is arguably in reach during extreme periods. Even though discouragement is belief-driven in the model, sufficiently tight loan terms and negative beliefs can depress the bank loan application utility enough that non-application due to discouragement becomes optimal the preferred choice even for medium-sized firms.

Figure 6 Scenarios with post-COVID bank loan availability beliefs for different firm sizes and supply levels (Scenarios 3 and 9)



Note: This figure extends the scenario analysis in Figure 6 by illustrating the interaction between post-COVID belief settings and changes in credit-supply conditions. Scenario 3 varies firm size, and Scenario 9 varies the BLS index for medium-sized firms. Utility indices are computed from the calibrated expected-utility representation (Equations 25–28) and normalized across outcomes. A Firm size of 0 denotes a medium-sized firm. Positive BLS Index values denote tighter lending standards.

5. Empirical investigation of bank loan application choices

5.1. Multinomial logit estimations of actual bank loan application behavior

We now turn from the calibrated indices to the empirical multinomial logit estimates of the four outcomes *{A, I, D, O}* on the common covariate set and the extended covariate set with previous application experience. Table 5 reports average marginal effects with clustered standard errors. We read these results through the lens of the mechanisms and thresholds developed above, investigating whether the signs and magnitudes align with the identified channels. Across both variable sets, application behavior behaves as the model predicts. The probability of applying is 7.5pp. to 11.2pp. higher for each level of firm size. Reported investment need leads to a 9.8pp. to 12.3 pp. increase in application probability. The size and investment effects are economically relevant and match the cost channel, i.e. bigger firms face lower effective costs, while investment plans potentially raise *R(I)*.

Discouragement is most sensitive to beliefs, especially lagged perceptions. Improved bank loan availability perceptions lead to a 3.4pp. to 5.2pp. lower probability of discouragement. Older and larger firms have about 2pp. lower probability of being discouraged for each age or size level increase. Firms that report the need for a bank loan for refinancing purposes are 2.2pp. to 3pp. more likely to be discouraged. This result aligns with the belief driven discouragement channels, but also hints at a fundamental channel we did not incorporate in our model. Firms that seek refinancing are potentially in a weaker financial situation and thus potentially legitimately discouraged.

For non-application due to other reasons, bigger firms have a 2.6 pp. to 3.9 pp. lower probability for each level of firm size increase. Stricter supply conditions are associated with about 2 pp. higher probability for non-application due to other reasons for a point increase in our BLS index. This confirms our proposed cost driven channel for non-application due to other reasons. Finally, for the internal funds category we see weak significance in one specification, showing a ≈2 pp. higher probability for the use of internal funds when past profits increase. Moreover, both investement and refinancing need substantially decrease the probability of relying on internal funds, consistent with our model calibration.

Turning to lagged experience, we find some indication of state persistence across all four potential bank loan application behavior categories. Prior internal funds-use strongly raises the probability of using internal funds again and lowers all alternatives. However, this implies that there is a certain share of firms that strongly prefer to avoid bank financing and rely on own retained earnings. Although these might be very healthy firms, economically such a behavior might be inefficient as especially such firms could drive investments. Prior discouragement increases current discouragement but also boosts application. A prior rejection has the largest positive effect on application and a negative effect on the use of internal funds, indicating unmet financing needs and learning-by-trying. However, a significant share of these firms also shifts to discouragement in the next period. Prior success likewise raises application in the next period and reduces all non-application categories. Firms that receive parts of funds needed also have the highest probability increase for another application in the next period, while having negative marginal effects on non-application behavior.

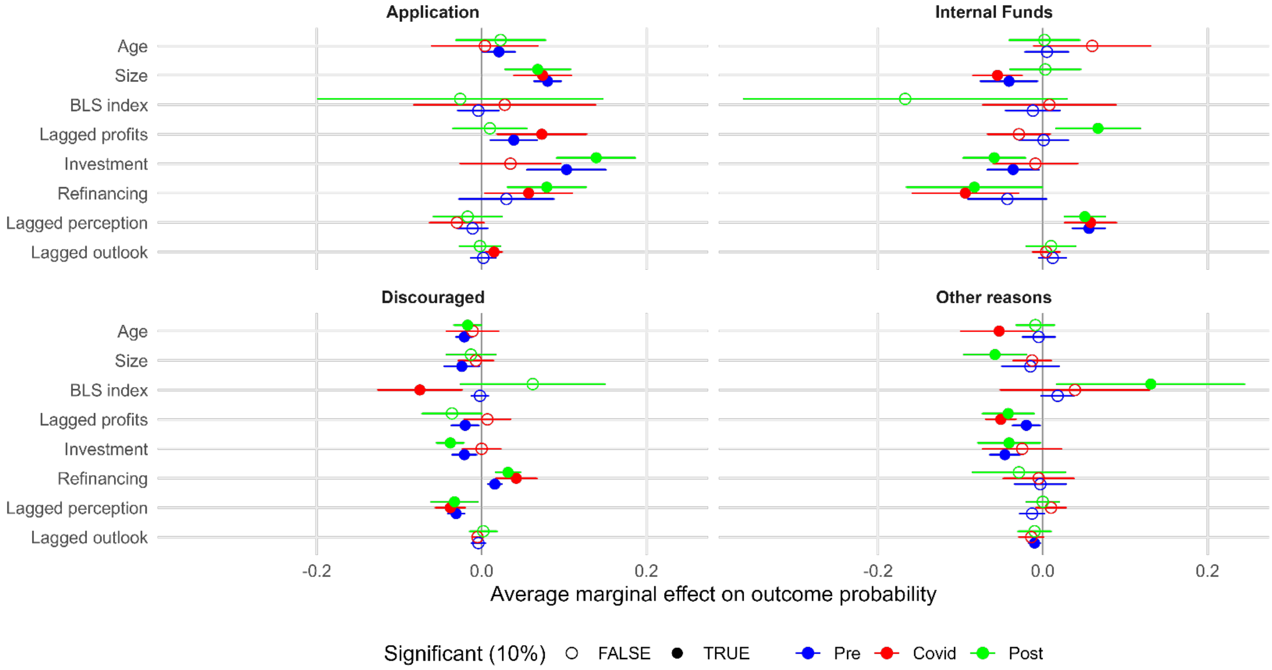
Table 5 Multinomial Logit results for the determinants of bank loan application decisions

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	−0.014	0.016	−0.020***	0.018	−0.016	0.021	−0.018***	0.013
	(0.013)	(0.014)	(0.004)	(0.018)	(0.012)	(0.013)	(0.005)	(0.017)
Size	−0.039***	0.112***	−0.028***	−0.045***	−0.026**	0.075***	−0.017**	−0.032**
	(0.012)	(0.012)	(0.010)	(0.016)	(0.012)	(0.008)	(0.008)	(0.015)
BLS Index	0.004	−0.011	0.007	−0.001	0.020*	−0.008	0.001	−0.012
	(0.015)	(0.023)	(0.006)	(0.023)	(0.011)	(0.018)	(0.006)	(0.019)
Lagged Profits	−0.029***	0.032**	−0.026**	0.023*	−0.032***	0.039***	−0.019*	0.011
	(0.006)	(0.012)	(0.010)	(0.012)	(0.006)	(0.013)	(0.010)	(0.013)
Investment	−0.042***	0.123***	−0.023***	−0.058***	−0.040***	0.098***	−0.020***	−0.039*
	(0.010)	(0.030)	(0.006)	(0.022)	(0.010)	(0.028)	(0.007)	(0.020)
Refinancing	−0.013	0.079**	0.030***	−0.096***	−0.011	0.051*	0.022***	−0.062**
	(0.014)	(0.033)	(0.004)	(0.036)	(0.012)	(0.029)	(0.004)	(0.031)
Lagged Perception	−0.007*	−0.023***	−0.052***	0.082***	−0.004	−0.017***	−0.034***	0.055***
	(0.004)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)	(0.007)	(0.008)
Lagged Outlook	−0.005	−0.002	−0.009	0.016**	−0.010***	0.005	−0.004	0.009
	(0.003)	(0.006)	(0.006)	(0.007)	(0.003)	(0.005)	(0.004)	(0.006)
Lagged Internal Funds					−0.089***	−0.026	−0.034***	0.149***
					(0.010)	(0.016)	(0.008)	(0.010)
Lagged Discouraged					−0.093***	0.095***	0.076***	−0.078***
					(0.013)	(0.024)	(0.007)	(0.023)
Lagged No Money					−0.085***	0.331***	0.041***	−0.288***
					(0.028)	(0.027)	(0.008)	(0.042)
Lagged Receive all					−0.111***	0.239***	−0.039***	−0.090***
					(0.013)	(0.014)	(0.014)	(0.012)
Lagged Receive parts					−0.094***	0.241***	0.002	−0.149***
					(0.019)	(0.020)	(0.010)	(0.018)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,333	7,333	7,333	7,333	6,891	6,891	6,891	6,891
Adjusted R^2	0.094	0.094	0.094	0.094	0.156	0.156	0.156	0.156
Log Likelihood	-8192.36	-8192.36	-8192.36	-8192.36	-7184.99	-7184.99	-7184.99	-7184.99

Notes: The table presents average marginal effects from multinomial logit estimations of SMEs' bank-loan application behavior. The dependent variable includes four mutually exclusive outcomes: *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (the base category). Columns 1–4 use the baseline covariate set; columns 5–8 add lagged experience with prior loan applications. Robust standard errors are clustered at the country level and reported in parentheses. Country, wave, and sector fixed effects are included in all specifications. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation.

As our time period covers the COVID pandemic and the subsequent interest rate hike, we re-estimate the multinomial logit separately for the pre-COVID (H1 2014 to H2 2019), COVID (H1 2020 to H1 2022), and post-COVID (H2 2022 to H1 2025) subsample. The full results are reported in Tables A4 to A5 in the Appendix. For ease of comparison, Figure 7 condenses the core determinants. It plots average marginal effects with 90% confidence intervals (Cis) for each outcome. Markers are coloured by period and filled when significant at the 10% level. Across subperiods the sign patterns and relative magnitudes of the main covariates are remarkably stable again reinforcing the robustness of our results. However, three notable patterns are visible here. First, the BLS index becomes statistically significant in the expected direction for non-application due to other reasons only in the post-COVID period. This coincides with the interest rate hike and tighter supply levels. Second, also only post-COVID, lagged profits become significant for Internal funds. Both results align with the changing interest rate environment and tighter refinancing conditions in the post-COVID period. Third, during COVID several coefficients attenuate or lose significance, a pattern plausibly explained by broad state interventions.

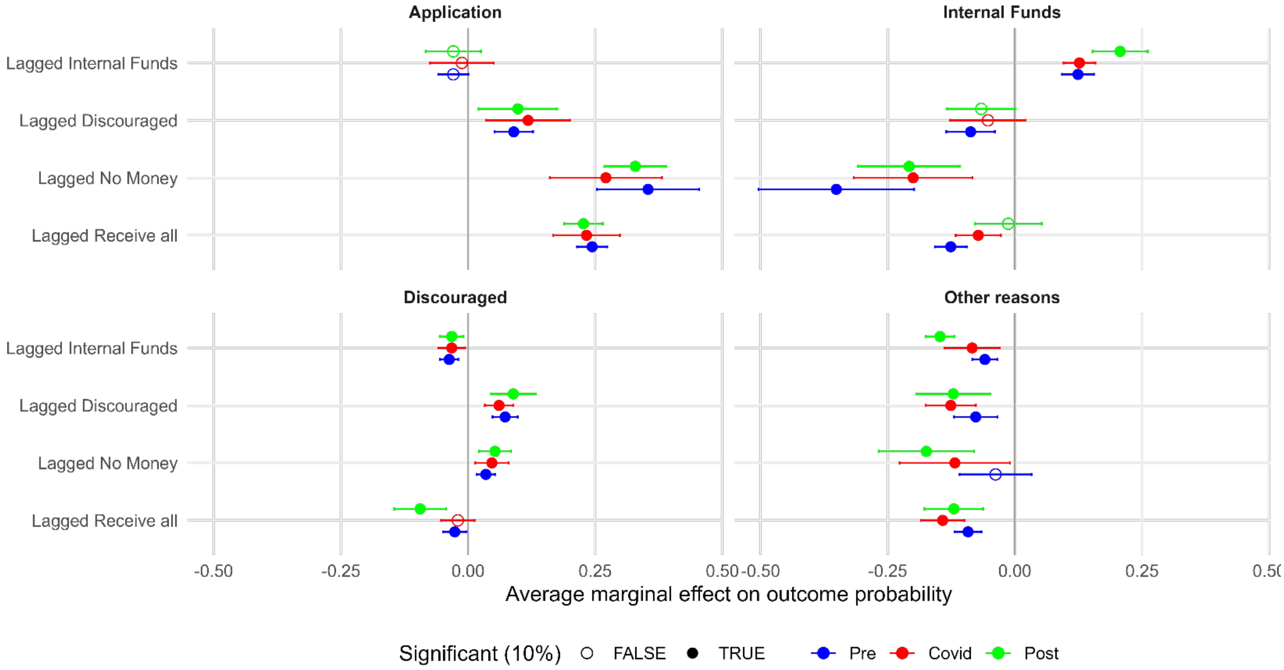
Figure 7 Determinants of bank loan application decisions across sample splits



Note: The figure summarizes the average marginal effects from period-specific multinomial logit estimations of bank-loan application behavior. Subsamples correspond to pre-COVID (H1 2014–H2 2019), COVID (H1 2020–H1 2022), and post-COVID (H2 2022–H1 2025) periods. Markers represent point estimates, with vertical lines showing 90% confidence intervals; filled markers denote statistical significance at the 10% level. Estimates are derived from the same specification as Table 5, including country, sector, and wave fixed effects.

Figure 8 plots period-specific average marginal effects of lagged outcomes, i.e. experience, on bank loan application choices. Across pre-, COVID, and post-COVID subsamples the patterns are consistent. The constancy of experience effects across periods implies that experience dynamics are structural, not regime-specific, and thus a potentially important measure for policy makers. E.g., interventions that turn first-time applications into successful experiences might durably shift future behavior, while interventions causing non-application might cause a persistent non-applying firm share.

Figure 8 Previous experience and the effect on bank loan application decisions across sample splits



Note: This figure plots period-specific average marginal effects of lagged outcomes (previous financing experience) on current bank-loan application behavior. Results are obtained from multinomial logit regressions estimated separately for the pre-COVID, COVID, and post-COVID periods, as defined in Figure 8. Markers indicate marginal effects with 90% confidence intervals. Estimates are derived from the same specification as Table 5, including country, sector, and wave fixed effects.

5.2. Shifting towards adverse non-application behavior

We next move to investigate shifts into negative non-application, i.e. a movement towards discouragement or non-application for other reasons. These shifting behaviors deserve specific attention as they capture forgone investment that arises either from pessimistic beliefs or from perceived borrowing costs and non-price frictions. Economically it is important to understand which factors are associated with such potentially inefficient movements. Focusing on shifts allows us to further test the mechanism mapping in Section 3 directly. Belief-driven movements should be influenced strongly by perception and outlook, whereas cost and terms-driven movements should be sensitive to firm size, age and our BLS index. We estimate logit specifications and report average marginal effects with results being presented in Table 6.

Consistent with the previous analytical steps, our estimates indicate a clear protection of larger, older and healthier firms against moving into discouragement as visible in specifications 1 to 3. One additional size category lowers the probability of a shift to discouragement by 1.8 pp. - 2.1 pp., and an extra age category by 1.1 - 1.2 pp. Better cash-flow as proxied by lagged profits reduces the probability of a shift by 1.6 pp. in the baseline. Investment plans are stabilizing, lowering the probability of discouragement by 1.5 - 1.9 pp. If the firm faces refinancing needs in contrary, this elevates the probability of a shift to discouragement by 2.0 - 2.5 pp. On the belief margin, perceptions are most important. An improvement in perceived availability reduces discouragement by 2.7 – 3.6 pp., thus constituting the strongest effect. This is in line with our suggested mechanism and as expected. Finally, prior experience again suggests strong path dependence.

Turning to shifts into non-application for other reasons, presented in columns 4–6, the patterns broadly mirror those for discouragement. Larger firms are less likely to move into this type of non-application with a one-category increase in size lowering the shift probability by 2.1 - 2.3 pp. Higher lagged profits reduce the probability of a shift by 1.3 pp. in the baseline. Investment plans remain stabilizing, reducing the shift probability by 2.2 - 2.5 pp. across specifications. A notable difference occurs for the refinancing need. Here, the coefficients are negative which the opposite sign to discouragement. Refinancing needs lower the probability of a shift to non-application due to other reasons by 0.8 – 2.1 pp.. This is an interesting finding as refinancing pressure, when it bites, pushes firms toward discouragement. Plausibly, because these are financially weaker firms for whom rejection risk is reasonably large and thus they opt-out of applying from their own insights. However, this might be an even economically efficient and beneficial mechanism of self-selection. Belief variables are small and insignificant, matching the idea that this outcome is driven by perceived costs and non-price frictions rather than beliefs. Finally, our BLS index is insignificant over the full sample but with expected signs in the full specifications. Although a bit contradicting our mechanism, this is unsurprising given that much of the period spans very low interest rates, easy lending policies and the pre-COVID policy regime, all of which likely muted cross-sectional variation in supply conditions. We return to this point in the split-sample analysis below, where post-COVID estimates recover the expected supply sensitivity.

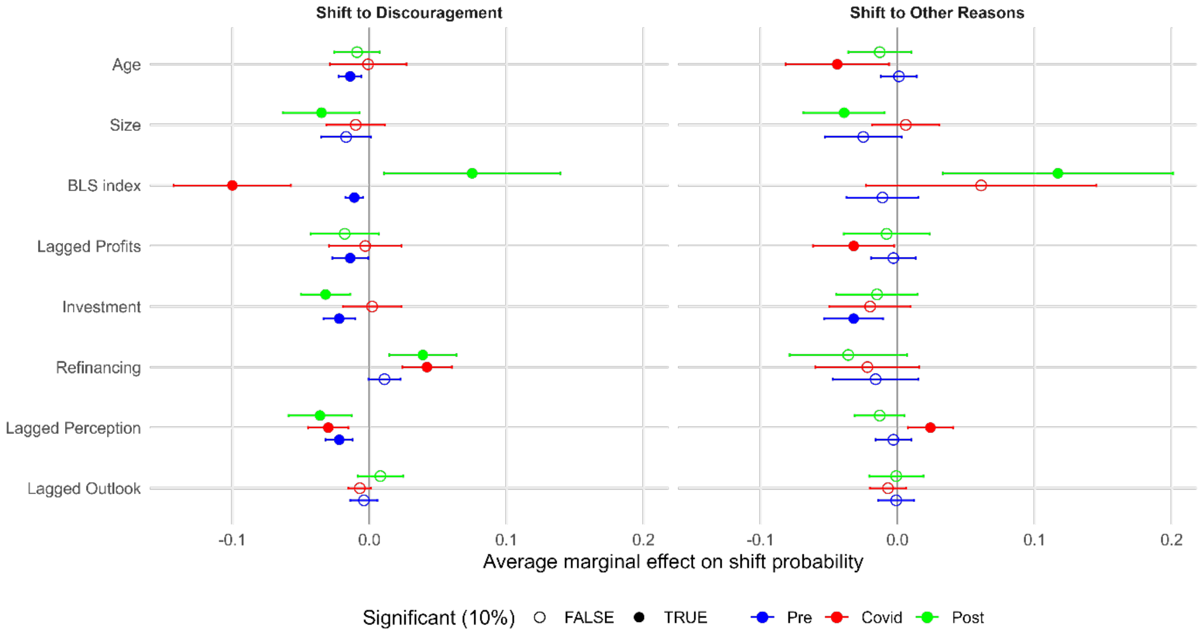
Table 6 Logit models for transition to discouragement or non-application due to other reasons

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.011*** (0.002)	-0.012** (0.004)	-0.012** (0.005)	−0.005* (0.003)	−0.011 (0.009)	−0.011 (0.008)
Size	-0.018*** (0.006)	-0.021** (0.008)	-0.019** (0.008)	−0.023*** (0.006)	−0.017* (0.009)	−0.021** (0.009)
BLS Index	0.007*** (0.002)	-0.004 (0.006)	-0.002 (0.006)	−0.001 (0.012)	0.007 (0.020)	0.007 (0.019)
Lagged Profits	-0.016*** (0.003)	-0.014 (0.009)	-0.013 (0.008)	−0.013*** (0.003)	−0.011 (0.007)	−0.009 (0.007)
Investment	-0.015*** (0.003)	-0.018*** (0.005)	-0.019*** (0.005)	−0.025** (0.010)	−0.022** (0.008)	−0.025*** (0.008)
Refinancing	0.020*** (0.003)	0.025*** (0.006)	0.022*** (0.005)	−0.008 (0.007)	−0.017** (0.008)	−0.021** (0.008)
Lagged Perception		-0.036*** (0.006)	-0.027*** (0.005)		0.001 (0.005)	0.002 (0.005)
Lagged Outlook		-0.003 (0.005)	-0.003 (0.004)		−0.005 (0.004)	−0.003 (0.004)
Lagged Internal Funds			-0.0305*** (0.006)			
Lagged No Money			0.025*** (0.006)			0.036** (0.015)
Lagged Receive all			0.030*** (0.011)			0.033*** (0.011)
Lagged Receive parts			0.001 (0.008)			0.053*** (0.012)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,512	6,387	6,387	30,512	6,387	6,387
Adjusted R^2	0.054	0.143	0.164	0.012	0.017	0.022
Log Likelihood	-4333.95	-1079.53	-1053.01	-11032.41	-2281.40	-2270.87

Notes: Lagged Discouragement is not included as covariate, as we are measuring the transition towards being discouraged. I.e. firms that were already discouraged are excluded from the estimation in all specifications. For the specifications 4 to 6 Lagged Non-Application for Other Reasons is excluded as well, as the base in this case is a shift towards non-application due to discouragement or for non-stated other reasons. We exclude enough internal funds as base category in all specifications. We report marginal effects. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Consistent with the previous multinomial logit exercise we estimate the pre-COVID, COVID and post-COVID sample splits for the shifts to Discouragement and Other Reasons for non-application. The full results are reported in Tables A7 to A9 in the Appendix. For ease of comparison, Figure 10 condenses the core determinants. The parameter patterns are broadly stable across periods, reinforcing that the main forces of shifting into negative non-application are size, previous cash-flow, investment need, and perceived bank loan availability. A salient change occurs in the supply conditions. The BLS index is insignificant pre-COVID and during COVID, but turns strongly positive and significant post-COVID. In that period, a one-unit tightening in our BLS index is associated with roughly 7.5 pp. higher probability of shifting to discouragement and even a 11.7 pp. higher probability of shifting to non-application for other reasons. This pattern is consistent with the mechanism mapping and reveals a relevant policy insight. Once the low-interest rate and COVID policy regimes recede, price and non-price terms become relevant drivers of SME application behavior and, more specifically, for shifting to non-application. Economically, the post-COVID sensitivity implies that marginal changes in lending standards can meaningfully reallocate firms across bank loan application decision alternatives.

Figure 9 Determinants of shifting behavior to non-application across sample splits



Note: This figure summarizes the estimated determinants of transitions into negative non-application states (*Discouraged* and *Other Reasons*) across pre-COVID (H1 2014–H2 2019), COVID (H1 2020–H1 2022), and post-COVID (H2 2022–H1 2025) periods. Estimates are drawn from the logit models in Table 6 and corresponding appendix tables (A7–A9). Bars represent marginal effects with 90% confidence intervals. The results highlight how size, profitability, investment need, and perceived credit availability drive non-application shifts, with post-COVID estimates showing heightened sensitivity to supply-side conditions (BLS index).

In sum, the analysis of shifting behaviors shows some clear patterns. Moves into discouragement are associated with firm scale, age, and cash-flow and with investment plans, but rise with refinancing pressure. However, beliefs exert the largest single effect, with negative availability perceptions materially increasing the likelihood of discouragement. Moves into non-application for other reasons are also less likely for larger, more profitable firms and in the presence of investment plans. This shift, consistent with our proposed mechanism is not belief-sensitive but rather consistent with a cost-driven channel. While our BLS index is insignificant in the full sample, the post-COVID sample split reveals strong supply sensitivity for both shifting decisions, confirming that tighter credit standards push firms away from applying. For policy, these results hold two major implications. First, for shifts into discouragement transparent communication on credit conditions, predictable policy paths, and targeted information and advisory programs, especially for small, young and refinancing-pressured firms, can reduce inefficient self-selection out of the application pool. Second, for shifts into non-application for other reasons a major priority is the supply environment. Although, supply conditions follow broader economic needs cautious explanation and additional information for smaller firms can lower effective borrowing frictions and keep viable applicants on the margin.

5.3. Robustness checks

To ensure the robustness of our findings, we conduct a series of robustness exercises. First, we provide additional insights to our expected utility scenario modelling and extend the set of calibrated scenarios in Appenidx B. The results confirm the same qualitative mechanisms. Size and investment plans systematically reduce the probability of negative non-application, while beliefs and perceptions remain the dominant drivers of discouragement.

To further ensure the robustness of our empirical results, we additionally estimate the multinomial logit specifications with the categorical variables (size, age, perception and outlook) being one-hot encoded. Here, the middle category each, serves as base category[11]. The estimations confirm the results presented in the main body of the text and can be found in Table C1 in the appendix. We also explore heterogeneity by estimating the multinomial logit separately for Northern and Southern European countries which can be found in tables C2 and C3 in the appendix. The broad patterns are very similar across both subsamples, but some notable differences emerge. In the Southern sample, firm size exhibits a markedly stronger effect, with marginal effects more than twice as large as in the North. Furthermore, refinancing needs increase discouragement probabilities in both groups, but the effect is more pronounced in the South. This might align with even tighter financing conditions and higher baseline vulnerabilities. Other coefficients remain stable, supporting the general robustness of our mechanism mapping.

Finally, we calculate transition probabilities before and after COVID to assess the persistence and dynamics of firm behavior. The results reveal that in the post-COVID environment, substantially fewer SMEs apply for bank loans, and this decline is particularly pronounced among smaller firms. This reinforces the view that adverse expectations and tighter supply disproportionately weigh on the most vulnerable segment of the SME population. Taken together, the robustness exercises corroborate our central conclusions.

6. Conclusions

This study acknowledges that non-application behavior for bank loans among European SMEs is economically more prevalent than loan application rejections by banks. We, therefore, investigate bank loan application and non-application behavior of SMEs in the Euro area, placing particular emphasis on why firms refrain from applying for loans and how these decisions differ across motives. Using data from the SAFE survey and the BLS, we can distinguish between situations in which firms do not apply for bank loans because they (1) rely on internal funds, (2) refrain for other reasons, or (3) become discouraged. By embedding these outcomes in an expected-utility framework and testing them empirically with multinomial logit models, we highlight the mechanisms behind the different types of non-application behavior. These mechanisms received so far limited attention in the literature.

We find that non-application for bank loans is not a residual state but shaped by heterogeneous drivers. First, reliance on bank funding and internal funds is largely consistent with standard investment theory and firm health. Larger and healthier firms with investment plans are more likely to apply for a bank loan. By contrast, smaller and younger firms seek substantially less bank loans, which is even reinforced in the post-COVID period. Second, discouragement is mainly driven by rational inattention and refinancing needs. Negative perceptions of loan availability substantially raise the probability of discouragement, while positive experiences foster persistence in applying. This “belief-driven channel” explains much of the variation in discouragement and highlights the path dependence of application behavior. However, firms with refinancing needs are

[11] Encoding such categorical variables is always a matter of underlying assumptions. Our standard coding assumes a strict preference structure with equidistant nature between the categories. By construction this assumption is a strong simplification of the reality. Therefore, we conduct a second estimation with these categories being coded as binaries. I.e. each of these variables is split into three distinct binary variables according to the previous categories. The middle category (0 in the original coding) is omitted in the estimations and therefore serves as baseline.

potentially weaker firms and their discouragement can reflect their prospects on the lending market. Third, other non-application reasons are more closely linked to perceived costs and supply conditions. After a decade of easy supply and low interest rates, higher interest rates and tighter credit conditions reinforced the role of the supply side after the COVID pandemic. Our interpretation of non-application as a sequential yet internally consistent process aligns with rational-inattention theory (Sims 2003; Matejka & McKay 2015). Firms do not ignore the loan market randomly but optimally limit costly information acquisition. Consequently, belief-driven discouragement can be seen as a rational response under bounded information capacity, while cost-driven non-application reflects fully processed but economically unfavorable terms.

These findings translate into potential policy implications. Preserving favorable and, more importantly, predictable and transparent lending conditions is key to preventing economically inefficient non-application. Even modest tightening of supply conditions can trigger sharp increases in discouragement and a substantial reduction in loan applications, especially among smaller firms. Moreover, targeted interventions to counteract negative perceptions are essential. One successful example is outlined and tested in Ferrando & Mulier (2022). They refer to a legal change in Belgium in 2014 that reduced firms' loan application costs. Transparent communication of lending standards and the promotion of positive borrowing experiences, e.g. through public guarantee schemes or improved feedback channels, can mitigate belief-driven discouragement and reduce the "stickiness" of past negative experiences.

Reducing discouragement is a matter of fairness in credit access but also a matter of macroeconomic efficiency. Discouraged firms invest substantially less than comparable applicants, implying that self-exclusion translates into forgone investment, and weaker productivity growth. Finally, particular attention should be given to firms with refinancing needs, as these are at heightened risk of discouragement. That said, they may be discouraged for economically justified reasons. Differentiating between inefficient discouragement and self-selection due to weak fundamentals should guide the design of support programs, ensuring that viable but constrained SMEs are not excluded from credit markets.

Our study also faces certain limitations. While the SAFE provides rich information on application behavior and non-application motives, it does not include detailed firm-level financials, which restricts the precision of some controls. Moreover, our expected-utility framing necessarily simplifies the formation of perceptions and beliefs, which may be shaped by additional firm-internal or sector-specific factors. Future research could combine survey evidence with balance-sheet data to disentangle financial fundamentals from behavioral influences and further explore how different shocks affect discouragement dynamics across firm types. Future work could also quantify the macroeconomic implications of non-application behavior by linking firm-level investment responses to aggregate outcomes. Taken together, however, our results underline that SME access to finance is not only determined by supply and demand fundamentals but also by perceptions, expectations, and past experiences. A policy agenda that pairs traditional credit instruments with belief-aware communication and post-shock review protocols can curb inefficient non-application and ultimately support SME investment and growth.

References

Alfaro, L., García-Santana, M., & Moral-Benito, E. (2021). On the direct and indirect real effects of credit supply shocks. Journal of Financial Economics, 139(3), 895-921.

Amore, M. D., Schneider, C., & Žaldokas, A. (2013). Credit supply and corporate innovation. Journal of financial economics, 109(3), 835-855.

Anastasiou, D., Kallandranis, C., & Drakos, K. (2022). Borrower discouragement prevalence for Eurozone SMEs: Investigating the impact of economic sentiment. Journal of Economic Behavior & Organization, 194, 161-171.

Andrieu, G., R. Staglianò, and P. van der Zwan. (2018). “Bank Debt and Trade Credit for SMEs in Europe: Firm-Industry-And Country-Level Determinants.” Small Business Economics 51 (1): 245−64.

Aristei, D., & Angori, G. (2022). Heterogeneity and state dependence in firms’ access to bank credit. Small Business Economics, 59(1), 47-78.

Bachas, N., Kim, O. S., & Yannelis, C. (2021). Loan guarantees and credit supply. Journal of Financial Economics, 139(3), 872-894.

Barrero, J. M. (2022). The micro and macro of managerial beliefs. Journal of Financial Economics, 143(2), 640-667.

Beck, T., Demirgüç-Kunt, A., & Maksimovic, V. (2008). Financing patterns around the world: Are small firms different?. Journal of financial economics, 89(3), 467-487.

Becker, B., & Ivashina, V. (2014). Cyclicality of credit supply: Firm level evidence. Journal of Monetary Economics, 62, 76-93.

Berg, T. (2018). Got rejected? Real effects of not getting a loan. The Review of Financial Studies, 31(12), 4912-4957.

Berger, A. N., & Udell, G. F. (2006). A more complete conceptual framework for SME finance. Journal of Banking & Finance, 30(11), 2945-2966.

Bernanke, B. S. (2020). The new tools of monetary policy. American Economic Review, 110(4), 943-983.

Bianchi, F., Ludvigson, S. C., & Ma, S. (2022). Belief distortions and macroeconomic fluctuations. American Economic Review, 112(7), 2269-2315.

Canton, E., Grilo, I., Monteagudo, J., & van der Zwan, P. (2013). Perceived credit constraints in the European Union. Small Business Economics, 41(3), 701-715.

Carroll, C. D. (2003). Macroeconomic expectations of households and professional forecasters. the Quarterly Journal of economics, 118(1), 269-298.

Cavallo, A., Cruces, G., & Perez-Truglia, R. (2017). Inflation expectations, learning, and supermarket prices: Evidence from survey experiments. American Economic Journal: Macroeconomics, 9(3), 1-35.

Cavalluzzo, K. S., Cavalluzzo, L. C., & Wolken, J. D. (2002). Competition, small business financing, and discrimination: Evidence from a new survey. The Journal of Business, 75(4), 641-679.

Chakravarty, S., & Xiang, M. (2013). The international evidence on discouraged small businesses. Journal of Empirical Finance, 20, 63-82.

Chittenden, F., Hall, G., & Hutchinson, P. (1996). Small firm growth, access to capital markets and financial structure: Review of issues and an empirical investigation. Small business economics, 8, 59-67.

Coluzzi, C., Ferrando, A., & Martinez-Carrascal, C. (2015). Financing obstacles and growth: an analysis for euro area non-financial firms. The European Journal of Finance, 21(10-11), 773-790.

Cowling, M., & Sclip, A. (2023). Dynamic discouraged borrowers. British Journal of Management, 34(4), 1774-1790.

Danielson, M. G., & Scott, J. A. (2004). Bank loan availability and trade credit demand. Financial Review, 39(4), 579-600.

Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., & Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. Journal of Financial Intermediation, 40, 100813.

De Haan, L., & Hinloopen, J. (2003). Preference hierarchies for internal finance, bank loans, bond, and share issues: evidence for Dutch firms. Journal of Empirical Finance, 10(5), 661-681.

De Meza, D., & Southey, C. (1996). The borrower's curse: optimism, finance and entrepreneurship. The Economic Journal, 106(435), 375-386.

Dell'Ariccia, G., Igan, D., & Laeven, L. U. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. Journal of Money, Credit and Banking, 44(2-3), 367-384.

De Marzo, P. M., Fishman, M. J., He, Z., & Wang, N. (2012). Dynamic agency and the q theory of investment. The journal of Finance, 67(6), 2295-2340.

Dimou, M., Ferrando, A., Köhler-Ulbrich, P., & Rariga, J. (2025). Insights from banks and firms on euro area credit conditions: a comparison based on ECB surveys. Economic Bulletin Boxes, 2.

Drexler, A., Fischer, G., & Schoar, A. (2014). Keeping it simple: Financial literacy and rules of thumb. American Economic Journal: Applied Economics, 6(2), 1-31.

Eurostat (2022). EU small and medium-sized enterprises: an overview. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/edn-20220627-1 (retrieved: 06.12.2023)

Ferrando, A., & Mulier, K. (2022). The real effects of credit constraints: Evidence from discouraged borrowers. Journal of Corporate Finance, 73, 102171.

Fidrmuc, J., Hainz, C., & Hölzl, W. (2024). Individual credit market experience and beliefs about bank lending policy: Evidence from a firm survey. Scandinavian Journal of Economics, forthcoming.

Fidrmuc, J., & Horky, F. (2023). Experience and Firms' Financing Behavior: A Behavioral Perspective. German Economic Review, forthcoming.

Fraser, S., & Nguyen, T. (2025). The Effects of Business Experience on Discouraged Borrowing and Efficiency in the Credit Market. British Journal of Management, forthcoming.

Grömping, U. (2007). Estimators of relative importance in linear regression based on variance decomposition. The American Statistician, 61(2), 139-147.

Hackbarth, D., Hennessy, C. A., & Leland, H. E. (2007). Can the trade-off theory explain debt structure?. The Review of Financial Studies, 20(5), 1389-1428.

Hernández-Cánovas, G., & Martínez-Solano, P. (2010). Relationship lending and SME financing in the continental European bank-based system. Small Business Economics, 34, 465-482.

Horky, F. (2024). SMEs' Perceptions of Availability of External Finance. Ekonomický časopis, 72(03-04), 105-139.

Hyun, J. S., & Rhee, B. K. (2011). Bank capital regulation and credit supply. Journal of Banking & Finance, 35(2), 323-330.

Kon, Y., & Storey, D. J. (2003). A theory of discouraged borrowers. Small business economics, 21, 37-49.

Kruskal, W. (1987). Relative importance by averaging over orderings. The American Statistician, 41(1), 6-10.

Lawrence, E. C., & Arshadi, N. (1995). A multinomial logit analysis of problem loan resolution choices in banking. Journal of Money, Credit and Banking, 27(1), 202-216.

Leary, M. T. (2009). Bank loan supply, lender choice, and corporate capital structure. The Journal of Finance, 64(3), 1143-1185.

Lin, H. (2011). Foreign bank entry and firms' access to bank credit: Evidence from China. Journal of Banking & Finance, 35(4), 1000-1010.

Lindeman, R. H., Merenda, P. F., & Gold, R. Z. (1980). Introduction to bivariate and multivariate analysis (Vol. 4). Glenview, IL: Scott, Foresman.

Matějka, F., & McKay, A. (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review*, *105*(1), 272-298.

Martinez, L. B., Guercio, M. B., & Bariviera, A. F. (2022). A meta-analysis of SMEs literature based on the survey on access to finance of enterprises of the European central bank. International Journal of Finance & Economics, 27(2), 1870-1885.

Massenot, B., & Pettinicchi, Y. (2018). Can firms see into the future? Survey evidence from Germany. Journal of Economic Behavior & Organization, 145, 66-79.

Mitchell, K., & Pearce, D. K. (2020). How did unconventional monetary policy affect economic forecasts?. Contemporary Economic Policy, 38(1), 206-220.

Moro, A., Fink, M., & Maresch, D. (2015). Reduction in information asymmetry and credit access for small and medium-sized enterprises. Journal of Financial Research, 38(1), 121-143.

Moscarini, G. (2004). Limited information capacity as a source of inertia. Journal of Economic Dynamics and control, 28(10), 2003-2035.

Orgler, Y. E. (1970). A credit scoring model for commercial loans. Journal of money, Credit and Banking, 2(4), 435-445.

Roger, T., Roger, P., & Schatt, A. (2018). Behavioral bias in number processing: Evidence from analysts' expectations. Journal of Economic Behavior & Organization, 149, 315-331.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: a stylized model of customer relationships. The Journal of Finance, 45(4), 1069–1087.

Sims, C. A. (2003). Implications of rational inattention. Journal of monetary Economics, 50(3), 665-690.

Véron, N., & Wolff, G. B. (2016). Capital Markets Union: a vision for the long term. Journal of Financial Regulation, 2(1), 130-153.

Appendix A: Additional Tables, Figures and Results

Table A1 Excerpt from the SAFE for constructing the main variables

Question	Possible answers
Application	
Have you applied for the following types (bank loan) of financing in the past six months? (Please take into account renewal of the existing contracts)	1) Applied 2) Did not apply because of possible rejection 3) Did not apply because of sufficient internal funds 4) Did not apply for other reasons 9) Don't know/not available
Experience	
If you applied and tried to negotiate for this type of financing over the past six months, what was the outcome? Please provide a separate answer in each case.	1) Received everything 5) Received 75% and above 6) Received below 75% 3) Refused because the cost was too high 4) Was rejected 8) Application is still pending 9) Don't know/not available
Perception	
For each of the following types of financing, would you say that their availability has improved, remained unchanged or deteriorated for your enterprise over the past six months?	1) Improved 2) Remained unchanged 3) Deteriorated 7) Instrument not applicable to my company 9) Don't know/not available
Expectation	
Looking ahead, for each of the following types of financing available to your enterprise, please indicate whether you think their availability will improve, deteriorate or remain unchanged over the next six months.	1) Improved 2) Remained unchanged 3) Deteriorated 7) Instrument not applicable to my company 9) Don't know/not available
Profits	
Have the following company indicators (Profit – net income after tax) decreased, remained unchanged or increased over the past six months?	1) Improved 2) Remained unchanged 3) Deteriorated 7) Instrument not applicable to my company 9) Don't know/not available
Investment	
For what purpose was financing used by your enterprise during the past six months? - Investments in property, plant or equipment	1) Yes 2) No 99) Don't know/not available
Refinancing	
For what purpose was financing used by your enterprise during the past six months? - Refinancing or paying off obligations	1) Yes 2) No 99) Don't know/not available
Size	
How many people does your enterprise currently employ either full or part-time at all its locations? Please do not include unpaid family workers and freelancers working regularly for your enterprise.	1) From 1 to 9 Employees 2) From 10 to 49 Employees 3) From 50 to 249 Employees 4) More than 250 Employees

	99) Don't know/not available
Age	
How many people does your enterprise currently employ either full or part-time at all its locations? Please do not include unpaid family workers and freelancers working regularly for your enterprise.	1) 10 years or more 2) 5 years or more, but less than 10 years 3) 2 years or more, but less than 5 years 4) Less than 2 years 99) Don't know/not available

Notes: For the Experience, answers 5 and 6 are combined into the received parts category, answers 3 and 4 into the no money category. 8 and 9 are excluded. For perception and expectation, we code deteriorated as -1, remained unchanged as 0 and improved as 1. For profits, we are only interested in increased profits indicating a better financial situation. Thus, we code improved profits as 1 and else as 0. Investment and refinancing are also coded binary with yes equaling 1 and no equaling 0. For the size we merge together answers 1 and 2 as small firms. Then, small firms are coded as -1, medium-sized firms as 0 and large firms as 1. Similarly for age we take together answers 3 and 4 as young firms and then code young firms as -1, medium-aged firms as 0 and older firms as 1. Don't know, not available, and not applicable are generally excluded from our variable generation.

Table A2 Correlation matrix

	Internal Funds	Discour.	Other Reasons	No Money	Received all	Received Parts	age	size	Bls index
Internal Funds	1.00	-0.23	-0.40	-0.18	-0.42	-0.21	-0.01	0.01	0.02
Discour.	-0.23	1.00	-0.15	-0.07	-0.15	-0.08	-0.02	-0.11	0.08
Other Reasons	-0.40	-0.15	1.00	-0.12	-0.26	-0.13	0.00	-0.09	0.01
No Money	-0.18	-0.07	-0.12	1.00	-0.12	-0.06	-0.02	-0.05	0.00
Received all	-0.42	-0.15	-0.26	-0.12	1.00	-0.14	0.02	0.14	-0.07
Received Parts	-0.21	-0.08	-0.13	-0.06	-0.14	1.00	0.02	0.05	-0.02
age	-0.01	-0.02	0.00	-0.02	0.02	0.02	1.00	0.10	0.00
sizel	0.01	-0.11	-0.09	-0.05	0.14	0.05	0.10	1.00	-0.04
Bls index	0.02	0.08	0.01	0.00	-0.07	-0.02	0.00	-0.04	1.00
Profits	0.12	-0.12	-0.06	-0.06	0.04	-0.04	-0.02	0.09	-0.06
Investment	-0.02	-0.08	-0.04	0.00	0.11	0.00	-0.04	0.13	-0.07
Refinancing	-0.07	0.10	0.00	0.06	-0.05	0.06	0.00	0.01	0.06
Perception	0.16	-0.27	-0.09	-0.24	0.24	-0.05	0.00	0.14	-0.15
Outlook	0.13	-0.20	-0.03	-0.16	0.13	-0.06	-0.01	0.11	-0.19
industry	-0.04	-0.04	-0.04	-0.02	0.11	0.01	0.06	0.26	-0.08
construction	-0.01	0.02	0.00	0.02	-0.02	0.01	0.02	-0.04	0.01
services	0.03	0.00	0.05	-0.01	-0.08	-0.01	-0.07	-0.12	0.03
trade	0.02	0.03	-0.02	0.01	-0.02	0.00	0.00	-0.11	0.04

	Profits	Invest.	Refinanc.	Perception	Outlook	industry	Construc.	services	trade
Internal Funds	0.12	-0.02	-0.07	0.16	0.13	-0.04	-0.01	0.03	0.02
Discour.	-0.12	-0.08	0.10	-0.27	-0.20	-0.04	0.02	0.00	0.03
Other Reasons	-0.06	-0.04	0.00	-0.09	-0.03	-0.04	0.00	0.05	-0.02
No Money	-0.06	0.00	0.06	-0.24	-0.16	-0.02	0.02	-0.01	0.01
Received all	0.04	0.11	-0.05	0.24	0.13	0.11	-0.02	-0.08	-0.02
Received Parts	-0.04	0.00	0.06	-0.05	-0.06	0.01	0.01	-0.01	0.00
age	-0.02	-0.04	0.00	0.00	-0.01	0.06	0.02	-0.07	0.00
sizel	0.09	0.13	0.01	0.14	0.11	0.26	-0.04	-0.12	-0.11
Bls index	-0.06	-0.07	0.06	-0.15	-0.19	-0.08	0.01	0.03	0.04
Profits	1.00	0.09	-0.06	0.30	0.29	0.04	-0.02	0.00	-0.03
Investment	0.09	1.00	-0.07	0.12	0.09	0.08	0.00	0.03	-0.11
Refinancing	-0.06	-0.07	1.00	-0.13	-0.10	-0.04	0.03	0.01	0.01
Perception	0.30	0.12	-0.13	1.00	0.69	0.10	-0.03	-0.04	-0.03
Outlook	0.29	0.09	-0.10	0.69	1.00	0.07	-0.02	-0.03	-0.02
industry	0.04	0.08	-0.04	0.10	0.07	1.00	-0.20	-0.48	-0.37
construction	-0.02	0.00	0.03	-0.03	-0.02	-0.20	1.00	-0.25	-0.19
services	0.00	0.03	0.01	-0.04	-0.03	-0.48	-0.25	1.00	-0.44
trade	-0.03	-0.11	0.01	-0.03	-0.02	-0.37	-0.19	-0.44	1.00

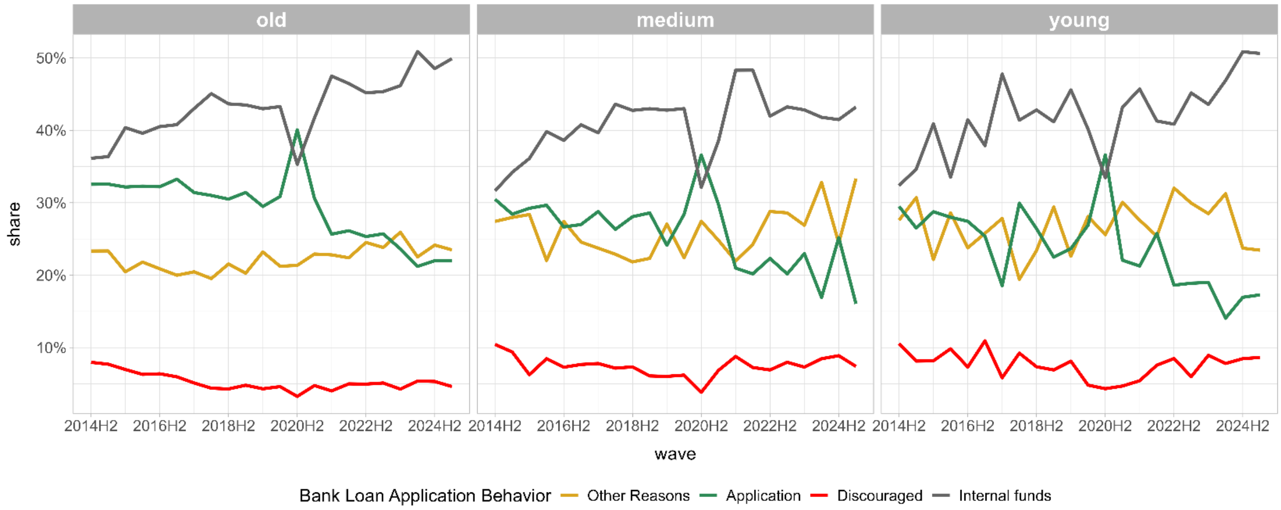
Note: This table reports pairwise Pearson correlations among the main explanatory variables used in the empirical analysis. Correlations are computed using complete observations only.

Table A3 Sector, country and wave composition of the sample

		Count		Share (%)
Sector	**241,519**		**100**	
Construction		21,868		9.05
Industry		41,208		17.06
Services		75,128		31.11
Trade		46,418		19.21
Other		56,897		23.56
Country	**241,519**		**100**	
AT		13,534		5.6
BE		13,788		5.71
	CY	*1,055*		*0.44*
DE		30,455		12.61
	EE	*1,034*		*0.43*
ES		29,576		12.25
FI		10,606		4.39
FR		31,644		13.1
GR		13,979		5.79
IE		10,771		4.46
IT		32,739		13.56
	LT	*3,120*		*1.29*
	LU	*1,048*		*0.43*
	LV	*2,078*		*0.86*
	MT	*1,076*		*0.45*
NL		18,824		7.79
PT		13,986		5.79
	SI	*2,054*		*0.85*
SK		10,152		4.2
Wave	**241,519**		**100**	
11		11,051		4.58
12		11,720		4.85
13		11,226		4.65
14		11,725		4.85
15		11,233		4.65
16		11,724		4.85
17		11,202		4.64
18		11,733		4.86
19		11,020		4.56
20		11,722		4.85
21		11,204		4.64
22		11,236		4.65
23		11,019		4.56
24		11,007		4.56
25		10,493		4.34
26		10,950		4.53
27		10,984		4.55
28		10,983		4.55
29		11,222		4.65
30		10,062		4.17
32		8,826		3.65
34		9,177		3.8

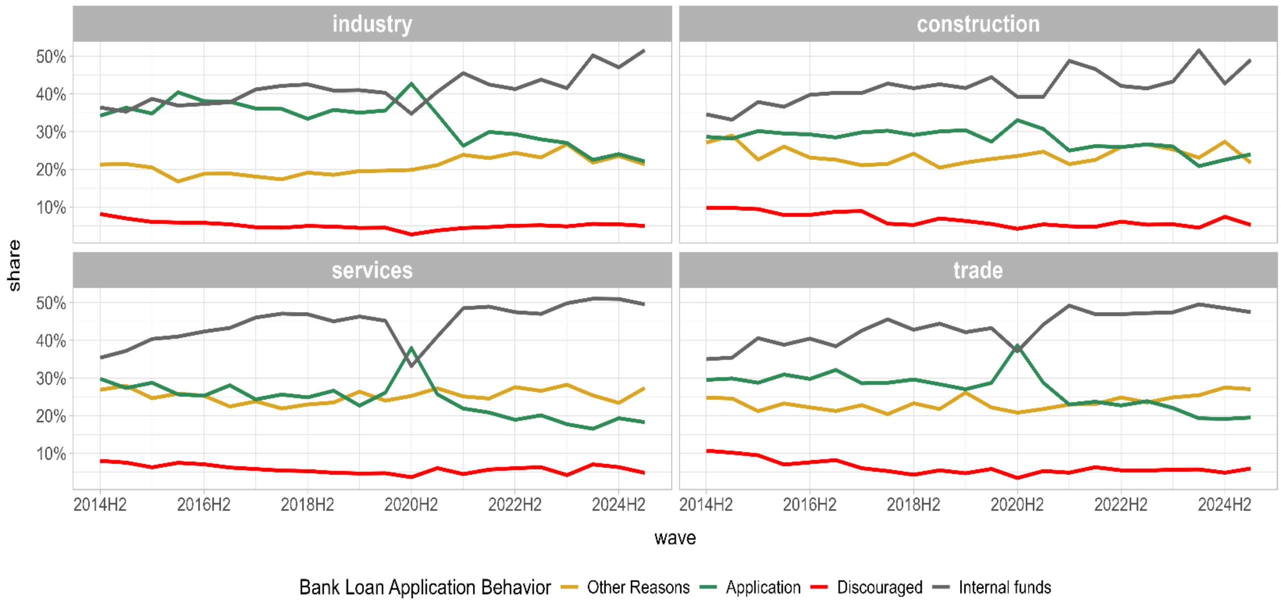
Note: This table provides definitions and data sources for all variables used in the empirical analysis. Firm-level characteristics, perceptions, and outlooks are taken from the ECB/EC *Survey on the Access to Finance of Enterprises* (SAFE). Credit-supply conditions are drawn from the ECB *Bank Lending Survey* (BLS) and standardized at the country–time level. Derived indicators (e.g., lagged profits, investment and refinancing needs) follow the coding described in Section 2 of the paper. The countries in italics only conduct the SAFE once a year. Thus, they are excluded whenever we use lagged variables but included in the stylized facts. In sum, these countries account for less than 5% of all observations.

Figure A1 Bank Loan Application behavior over time by firm age



Note: The figure plots SMEs' loan-application outcomes by firm age category (young, mature, and old) across SAFE waves 11–34 (2014H1–2025H1). Shares are computed within each age group and survey wave. Categories sum to 100% within each group. The sample includes euro-area firms from 19 countries with continuous SAFE coverage.

Figure A2 Bank Loan Application behavior over time by firm sector



Note: This figure presents the evolution of bank-loan application behavior by sector (manufacturing, construction, trade, and services) using SAFE waves 11–34 (2014H1–2025H1). Shares are calculated within each sector and wave. Categories sum to 100%. The data show limited sectoral variation except during the initial COVID-19 wave, when construction did not exhibit the application spike observed in other sectors.

Table A4 Multinomial Logit results for the pre-COVID period (2014 Q4 to 2019 Q4)

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	-0.006	0.019	-0.023***	0.009	-0.005	0.021*	-0.021***	0.005
	(0.014)	(0.015)	(0.005)	(0.019)	(0.012)	(0.012)	(0.006)	(0.016)
Size	-0.030	0.126***	-0.037**	-0.060***	-0.015	0.080***	-0.024*	-0.041*
	(0.019)	(0.015)	(0.015)	(0.021)	(0.021)	(0.010)	(0.013)	(0.021)
BLS Index	0.003	-0.013	0.005	0.006	0.018	-0.004	-0.002	-0.012
	(0.015)	(0.019)	(0.006)	(0.021)	(0.012)	(0.015)	(0.006)	(0.020)
Lagged Profits	-0.018**	0.035**	-0.029***	0.011	-0.020**	0.039**	-0.020**	0.001
	(0.009)	(0.016)	(0.010)	(0.017)	(0.010)	(0.017)	(0.010)	(0.018)
Investment	-0.044***	0.125***	-0.025***	-0.056***	-0.046***	0.103***	-0.021**	-0.036*
	(0.013)	(0.033)	(0.009)	(0.022)	(0.011)	(0.029)	(0.009)	(0.019)
Refinancing	-0.011	0.058	0.024***	-0.071**	-0.003	0.030	0.016***	-0.043
	(0.021)	(0.039)	(0.005)	(0.036)	(0.019)	(0.035)	(0.005)	(0.029)
Lagged Perception	-0.015**	-0.022*	-0.047***	0.084***	-0.013	-0.011	-0.031***	0.056***
	(0.006)	(0.013)	(0.009)	(0.011)	(0.009)	(0.011)	(0.006)	(0.012)
Lagged Outlook	-0.005	-0.006	-0.011*	0.022**	-0.010**	0.002	-0.004	0.012
	(0.004)	(0.010)	(0.006)	(0.011)	(0.004)	(0.009)	(0.005)	(0.010)
Lagged Internal Funds					-0.059***	-0.029	-0.037***	0.124***
					(0.015)	(0.018)	(0.011)	(0.019)
Lagged Discouraged					-0.077***	0.090***	0.073***	-0.087***
					(0.026)	(0.023)	(0.015)	(0.029)
Lagged No Money					-0.038	0.354***	0.035***	-0.351***
					(0.043)	(0.061)	(0.011)	(0.093)
Lagged Receive all					-0.092***	0.244***	-0.026*	-0.126***
					(0.016)	(0.018)	(0.014)	(0.019)
Lagged Receive parts					-0.086***	0.288***	0.004	-0.206***
					(0.019)	(0.025)	(0.016)	(0.027)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,079	4,079	4,079	4,079	3,831	3,831	3,831	3,831
Adjusted R^2	0.110	0.110	0.110	0.110	0.178	0.178	0.178	0.178
Log Likelihood	-4396.24	-4396.24	-4396.24	-4396.24	-3820.53	-3820.53	-3820.53	-3820.53

Note: This table reports marginal effects from the multinomial logit model of SMEs' bank-loan application behavior estimated on the pre-COVID subsample (H1 2014–H2 2019). The dependent variable includes *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (base category). Robust standard errors clustered at the country level are shown in parentheses. Country, wave, and sector fixed effects are included in all specifications. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for Other Reasons are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's mlogit command and margins postestimation.

Table A5 Multinomial Logit results for the COVID period (2020 Q2 to 2022 Q2)

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	-0.044*	-0.019	-0.006	0.070	-0.053*	0.004	-0.011	0.060
	(0.024)	(0.041)	(0.020)	(0.044)	(0.028)	(0.039)	(0.019)	(0.043)
Size	-0.016	0.096***	-0.021*	-0.059***	-0.013	0.074***	-0.007	-0.055***
	(0.015)	(0.020)	(0.012)	(0.017)	(0.014)	(0.021)	(0.013)	(0.018)
BLS Index	0.015	0.060	-0.063**	-0.013	0.039	0.028	-0.075**	0.008
	(0.064)	(0.066)	(0.031)	(0.046)	(0.055)	(0.067)	(0.031)	(0.049)
Lagged Profits	-0.032*	0.054*	0.002	-0.025	-0.051***	0.073**	0.007	-0.029
	(0.017)	(0.032)	(0.017)	(0.025)	(0.011)	(0.033)	(0.017)	(0.023)
Investment	-0.032	0.050	0.005	-0.023	-0.025	0.035	-0.000	-0.009
	(0.024)	(0.036)	(0.013)	(0.034)	(0.029)	(0.037)	(0.014)	(0.031)
Refinancing	-0.006	0.081**	0.042**	-0.116***	-0.005	0.057*	0.042**	-0.094**
	(0.029)	(0.035)	(0.017)	(0.037)	(0.026)	(0.032)	(0.015)	(0.039)
Lagged Perception	0.001	-0.023	-0.051***	0.073***	0.010	-0.030	-0.038***	0.058***
	(0.008)	(0.016)	(0.009)	(0.016)	(0.011)	(0.020)	(0.011)	(0.019)
Lagged Outlook	-0.011	0.007	-0.005	0.009	-0.014	0.015**	-0.005	0.004
	(0.012)	(0.005)	(0.003)	(0.009)	(0.009)	(0.006)	(0.004)	(0.010)
Lagged Internal Funds					-0.084**	-0.012	-0.032*	0.127***
					(0.033)	(0.038)	(0.016)	(0.019)
Lagged Discouraged					-0.126***	0.118**	0.061***	-0.053
					(0.030)	(0.050)	(0.017)	(0.045)
Lagged No Money					-0.118*	0.271***	0.047**	-0.200**
					(0.066)	(0.067)	(0.020)	(0.071)
Lagged Receive all					-0.142***	0.233***	-0.020	-0.072***
					(0.026)	(0.040)	(0.020)	(0.027)
Lagged Receive parts					-0.076	0.232***	0.010	-0.165**
					(0.047)	(0.047)	(0.020)	(0.063)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,556	1,556	1,556	1,556	1,469	1,469	1,469	1,469
Adjusted R^2	0.077	0.077	0.077	0.077	0.125	0.125	0.125	0.125
Log Likelihood	-1753.29	-1753.29	-1753.29	-1753.29	-1572.79	-1572.79	-1572.79	-1572.79

Note: This table presents average marginal effects from the multinomial logit estimation of SMEs' bank-loan application behavior during the COVID period (H1 2020–H1 2022). The dependent variable includes four mutually exclusive outcomes: *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (base category). Country, wave, and sector fixed effects are included in all models; robust standard errors clustered at the country level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation.

Table A6 Multinomial Logit results for the post-COVID interest-rate hike period (2022 Q4 to 2024 Q4)

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	-0.000	0.025	-0.020**	-0.004	-0.009	0.023	-0.017*	0.002
	(0.017)	(0.038)	(0.010)	(0.030)	(0.014)	(0.033)	(0.010)	(0.026)
Size	-0.074***	0.095***	-0.018	-0.003	-0.058**	0.068***	-0.013	0.003
	(0.025)	(0.020)	(0.019)	(0.031)	(0.023)	(0.024)	(0.018)	(0.026)
BLS Index	0.069	-0.004	0.051	-0.115	0.131*	-0.026	0.062	-0.167
	(0.067)	(0.123)	(0.048)	(0.140)	(0.069)	(0.105)	(0.053)	(0.119)
Lagged Profits	-0.050***	0.005	-0.044*	0.089***	-0.042**	0.010	-0.036	0.067**
	(0.018)	(0.028)	(0.024)	(0.027)	(0.019)	(0.027)	(0.022)	(0.031)
Investment	-0.048**	0.173***	-0.046***	-0.078***	-0.041*	0.139***	-0.038***	-0.059**
	(0.020)	(0.028)	(0.009)	(0.018)	(0.023)	(0.029)	(0.010)	(0.023)
Refinancing	-0.019	0.110***	0.040***	-0.131**	-0.029	0.079***	0.032***	-0.083*
	(0.031)	(0.038)	(0.012)	(0.052)	(0.034)	(0.029)	(0.009)	(0.050)
Lagged Perception	0.003	-0.031	-0.060***	0.088***	-0.000	-0.017	-0.033*	0.051***
	(0.012)	(0.020)	(0.013)	(0.013)	(0.012)	(0.025)	(0.017)	(0.015)
Lagged Outlook	-0.004	-0.010	-0.001	0.014	-0.010	-0.002	0.002	0.010
	(0.009)	(0.013)	(0.012)	(0.016)	(0.012)	(0.015)	(0.010)	(0.018)
Lagged Internal Funds					-0.147***	-0.029	-0.032**	0.207***
					(0.017)	(0.033)	(0.014)	(0.033)
Lagged Discouraged					-0.121***	0.098**	0.089***	-0.066
					(0.044)	(0.047)	(0.027)	(0.041)
Lagged No Money					-0.174***	0.329***	0.053***	-0.208***
					(0.057)	(0.037)	(0.019)	(0.061)
Lagged Receive all					-0.120***	0.227***	-0.094***	-0.013
					(0.035)	(0.023)	(0.031)	(0.040)
Lagged Receive parts						0.134***	-0.007	0.006
						(0.027)	(0.021)	(0.073)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,698	1,698	1,698	1,698	1,591	1,591	1,591	1,591
Adjusted R^2	0.089	0.089	0.089	0.089	0.156	0.156	0.156	0.156
Log Likelihood	-1951.86	-1951.86	-1951.86	-1951.86	-1696.62	-1696.62	-1696.62	-1696.62

Note: This table reports average marginal effects from multinomial logit estimations for the post-COVID period (H2 2022–H1 2025). The model specification follows Table 5, with the dependent variable covering *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (base category). All regressions include country, wave, and sector fixed effects; robust standard errors are clustered at the country level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation.

Table A7 Logit models for transition to discouragement or non-application due to other reasons for the pre-COVID period (2014 Q4 to 2019 Q4)

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.012***	-0.015***	-0.014***	−0.006	0.000	0.001
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.008)
Size	-0.017***	-0.017	-0.017	−0.027***	−0.022	−0.025
	(0.005)	(0.011)	(0.011)	(0.009)	(0.017)	(0.017)
BLS Index	0.000	-0.013***	-0.011**	−0.011	−0.013	−0.011
	(0.002)	(0.005)	(0.004)	(0.018)	(0.016)	(0.016)
Lagged Profits	-0.015***	-0.015*	-0.014*	−0.017***	−0.004	−0.003
	(0.004)	(0.008)	(0.008)	(0.004)	(0.010)	(0.010)
Investment	-0.016***	-0.021***	-0.022***	−0.023*	−0.030**	−0.032**
	(0.003)	(0.006)	(0.007)	(0.013)	(0.013)	(0.013)
Refinancing	0.018***	0.013	0.011*	−0.003	−0.013	−0.016
	(0.004)	(0.008)	(0.007)	(0.013)	(0.018)	(0.019)
Lagged Perception		-0.030***	-0.022***		−0.006	−0.003
		(0.007)	(0.006)		(0.009)	(0.008)
Lagged Outlook		-0.004	-0.004		−0.003	−0.001
		(0.006)	(0.006)		(0.008)	(0.008)
Lagged Internal Funds			-0.034***			
			(0.009)			
Lagged No Money			0.020*			0.053***
			(0.011)			(0.018)
Lagged Receive all			-0.021*			0.025**
			(0.011)			(0.011)
Lagged Receive parts			0.001			0.036***
			(0.012)			(0.013)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,443	3,533	3,533	16,443	3,533	3,533
Adjusted R^2	0.069	0.192	0.213	0.013	0.022	0.026
Log Likelihood	-2301.68	-525.85	-512.39	-5792.91	-1195.65	-1190.81

Notes: Lagged Discouragement is not included as covariate, as we are measuring the transition towards being discouraged. I.e. firms that were already discouraged are excluded from the estimation in all specifications. For the specifications 4 to 6 Lagged Non-Application for Other Reasons is excluded as well, as the base in this case is a shift towards non-application due to discouragement or for non-stated other reasons. We exclude enough internal funds as base category in all specifications. We report marginal effects. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A8 Logit models for transition to discouragement or non-application due to other reasons for the COVID period (2020 Q2 to 2022 Q2)

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.008*	-0.002	-0.001	−0.006	−0.044*	−0.044*
	(0.004)	(0.017)	(0.017)	(0.008)	(0.024)	(0.023)
Size	-0.020**	-0.014	-0.010	−0.020**	0.010	0.006
	(0.008)	(0.011)	(0.013)	(0.009)	(0.014)	(0.015)
BLS Index	-0.016	-0.099***	-0.100***	0.005	0.060	0.061
	(0.013)	(0.026)	(0.026)	(0.030)	(0.052)	(0.051)
Lagged Profits	-0.014*	-0.004	-0.003	−0.008	−0.033*	−0.032*
	(0.007)	(0.016)	(0.016)	(0.009)	(0.018)	(0.018)
Investment	-0.004	0.004	0.002	−0.030**	−0.018	−0.020
	(0.004)	(0.013)	(0.013)	(0.013)	(0.017)	(0.018)
Refinancing	0.017***	0.048***	0.042***	−0.006	−0.017	−0.022
	(0.004)	(0.011)	(0.011)	(0.012)	(0.022)	(0.023)
Lagged Perception		-0.039***	-0.030***		0.021**	0.024**
		(0.009)	(0.009)		(0.010)	(0.010)
Lagged Outlook		-0.007	-0.007		−0.009	−0.007
		(0.006)	(0.005)		(0.008)	(0.008)
Lagged Internal Funds			-0.029**			
			(0.013)			
Lagged No Money			0.035*			0.026
			(0.019)			(0.043)
Lagged Receive all			-0.015			0.006
			(0.017)			(0.020)
Lagged Receive parts			0.007			0.062**
			(0.018)			(0.023)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,997	1,387	1,387	6,997	1,387	1,387
Adjusted R²	0.037	0.164	0.185	0.015	0.029	0.033
Log Likelihood	-957.56	-231.71	-225.95	-2562.92	-519.72	-517.60

Notes: Lagged Discouragement is not included as covariate, as we are measuring the transition towards being discouraged. I.e. firms that were already discouraged are excluded from the estimation in all specifications. For the specifications 4 to 6 Lagged Non-Application for Other Reasons is excluded as well, as the base in this case is a shift towards non-application due to discouragement or for non-stated other reasons. We exclude enough internal funds as base category in all specifications. We report marginal effects. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table A9 Logit models for transition to discouragement or non-application due to other reasons for the post-COVID and interest-rate hike period (2022 Q4 to 2024 Q4)

	(1)	(2)	(3)	(4)	(5)	(6)
Age	-0.010**	-0.007	-0.009	−0.002	−0.011	−0.013
	(0.004)	(0.011)	(0.010)	(0.006)	(0.014)	(0.014)
Size	-0.016**	-0.039**	-0.035**	−0.017**	−0.031*	−0.039**
	(0.008)	(0.018)	(0.017)	(0.008)	(0.017)	(0.018)
BLS Index	0.006	0.068*	0.075*	0.041*	0.118**	0.117**
	(0.010)	(0.041)	(0.039)	(0.024)	(0.050)	(0.051)
Lagged Profits	-0.019**	-0.021	-0.018	−0.009	−0.006	−0.008
	(0.009)	(0.015)	(0.015)	(0.007)	(0.017)	(0.019)
Investment	-0.025***	-0.033***	-0.032***	−0.022***	−0.008	−0.015
	(0.004)	(0.009)	(0.011)	(0.008)	(0.016)	(0.018)
Refinancing	0.028***	0.044***	0.039**	−0.021	−0.032	−0.036
	(0.003)	(0.015)	(0.015)	(0.014)	(0.027)	(0.026)
Lagged Perception		-0.046***	-0.036**		−0.011	−0.013
		(0.011)	(0.014)		(0.011)	(0.011)
Lagged Outlook		0.011	0.008		−0.004	−0.001
		(0.010)	(0.010)		(0.012)	(0.012)
Lagged Internal Funds			-0.028***			
			(0.010)			
Lagged No Money			0.025			−0.003
			(0.017)			(0.039)
Lagged Receive all			-0.074***			0.067***
			(0.022)			(0.022)
Lagged Receive parts			0.004			0.075
			(0.019)			(0.046)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,072	1,467	1,467	7,072	1,467	1,119
Adjusted R²	0.065	0.123	0.151	0.017	0.023	0.034
Log Likelihood	-1041.55	-289.53	-280.30	-2649.70	-548.75	-542.30

Notes: Lagged Discouragement is not included as covariate, as we are measuring the transition towards being discouraged. I.e. firms that were already discouraged are excluded from the estimation in all specifications. For the specifications 4 to 6 Lagged Non-Application for Other Reasons is excluded as well, as the base in this case is a shift towards non-application due to discouragement or for non-stated other reasons. We exclude enough internal funds as base category in all specifications. We report marginal effects. Robust standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Appendix B: Additional Tables, Figures and Results

Core task in calibrating our model is to get the weights and contributions of the relevant observable variables:

$$\widehat{m}_A(x) = \sum_{k \in K_A} \omega_{A,k}\, s_{A,k} x_k,$$

In a standard linear regression model, the coefficients indicate the change in the predicted outcome for a one-unit change in a predictor. These coefficients, whether standardized or not, primarily relate to the predicted mean levels of the outcome. Contrastingly, general dominance statistics offer a different perspective. They partition the R-squared value, reflecting the full range of a predictor's values as they translate into the predicted outcome. The relative importance of each variable X_i in calculating $U_j(X)$ is then assessed using the LMG method. This method decomposes the total variance explained by the model into contributions attributable to each predictor.

$$Relative\ Importance\ of\ X_i = \frac{Variance\ explained\ by\ X_i}{Total\ Variance\ explained\ by\ the\ model}$$

Specifically we use the LMG method, as proposed by Grömping (2007). This method, also known as averaging over orderings evaluates the contribution of each predictor to the model's R^2 by considering all possible orders in which the predictors could be entered into the regression model. The LMG value is then calculated as:

$$LMG_{X_i} = \frac{1}{N!}\sum_{N!} \Delta R^2_{X_i},$$

where *N!* denotes all possible permutations. This LMG value is then given as a proportion of the total R^2 of the model. This approach considers the entire variance of the predictor simultaneously, rather than analyzing one unit of change at a time. Therefore, general dominance statistics are more concerned with the predicted spread or variation of the outcome rather than just mean level changes.

Table B1 presents our linear models which we use to extract the signs, while table B2 contains the weights for all variables.

Table B1 Linear Models to extract contribution

	Application	Internal Funds	Discouraged	Other Reasons
Size	0.076***	–0.017**	–0.022***	–0.038***
	(0.008)	(0.008)	(0.004)	(0.007)
Age	0.023*	0.014	–0.023***	–0.014
	(0.013)	(0.012)	(0.006)	(0.010)
Lagged Perception	–0.001	0.067***	–0.051***	–0.014**
	(0.009)	(0.008)	(0.004)	(0.007)
Lagged Outlook	0.009	0.004	–0.004	–0.009
	(0.008)	(0.008)	(0.004)	(0.007)
Lagged Profits	0.011	0.042***	–0.021***	–0.032***
	(0.013)	(0.012)	(0.006)	(0.010)
Investment Need	0.112***	–0.045***	–0.027***	–0.040***
	(0.012)	(0.011)	(0.006)	(0.009)
Refinancing Need	0.020	–0.057***	0.047***	–0.011
	(0.014)	(0.014)	(0.007)	(0.011)
BLS Index	–0.103***	0.054***	0.037***	0.012
	(0.020)	(0.020)	(0.010)	(0.016)
Observations	7,333	7,333	7,333	7,333
Adjusted R^2	0.036	0.027	0.074	0.017
F Statistic	35.086***	26.509***	74.757***	16.446***

Note: This table reports coefficient estimates from the linear probability models used to construct the expected-utility indices in Section 3.4 (Equations 19–20). Each model is estimated separately for one of the four behavioral outcomes: *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*. Regressions include the full common set of covariates xxx as defined in Equation (23). Standard errors are clustered at the country level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The estimated coefficients provide the basis for calculating variable signs and relative-importance weights summarized in Table 3.

Table B2 Relative importance of linear regressors

	Application	Internal Funds	Discouraged	Other Reasons
Size	0.386	0.015	0.077	0.340
Age	0.019	0.004	0.023	0.020
Lagged Perception	0.017	0.493	0.439	0.149
Lagged Outlook	0.023	0.177	0.179	0.115
Lagged Profits	0.015	0.116	0.073	0.148
Investment Need	0.419	0.062	0.066	0.208
Refinancing Need	0.005	0.104	0.096	0.004
BLS Index	0.113	0.024	0.045	0.015
Observations	7,333	7,333	7,333	7,333
Total Response Variance	0.239	0.227	0.067	0.147

Note: This table decomposes the model R^2 for each outcome (Application, Internal Funds, Discouraged, Other Reasons) into relative contributions of individual covariates using the Lindeman–Merenda–Gold (LMG) method (Lindeman et al., 1980; Grömping 2007). Values indicate each variable's share in explaining the total model variance. The decomposition corresponds to the models reported in Table B1 and underlies the sign-weight mapping in Table 3. SAFE waves 11–34 (2014H2–2025H1) are used.

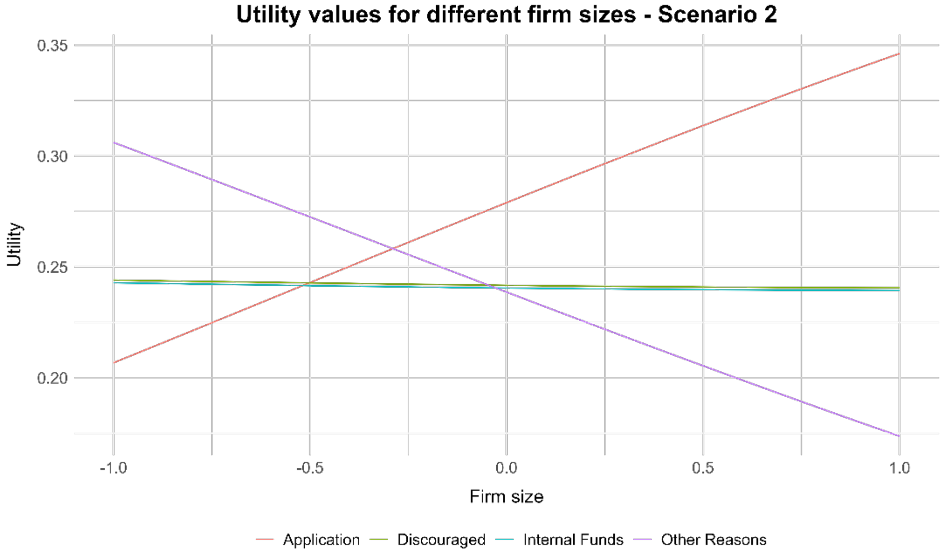
For our expected utility modelling approach, we need continuous variable ranges which are aligned with the variables and their ranges from the utilized surveys to ensure consistency. While the surveys usually contain discrete, categorical steps, we assume a continuous flow between these steps for modelling purposes.

Table B3 Composition and value range of the variables

Variable	Explanation	Range
Fix firm characteristics (F)		
size	Categorical variable indicating whether a firm is small (below 49 full-time employees), medium size (50 to 249 full-time employees) or large (>250 full-time employees). For modelling purposes, we code this as -1, 0 and 1.	-1 to 1
age	Categorical variable indicating whether a firm is young (below 5 years), medium (5 to 10 years) or old (>10 years). For modelling purposes, we code this as -1, 0 and 1.	-1 to 1
Needs (N)		
Investment	Binary variable, indicating whether the firm used financing for investment (1) or not (0).	0 to 1
Refinancing	Binary variable, indicating whether the firm used financing for refinancing or paying off obligations (1) or not (0).	0 to 1
Profits (P)		
Lagged Profits	Binary variable capturing past period profits development. I.e. whether the profits increased in the past period (1) or not (0).	0 to 1
Supply (S)		
BLS	Compound index (based on 5 individual questions) derived from the bank lending survey, capturing whether banks tightened or loosened their lending conditions. Negative values signify loosened lending conditions, positive values signify tightened lending conditions. The index is normalized between -1 and 1	-1 to 1
Behavioral factors (B)		
Lagged Perception	Categorical variable capturing the past periods availability perception of bank loans of a firm, where -1 indicates a deteriorated perception, 0 a neutral perception and 1 an improved perception.	-1 to 1
Lagged Outlook	Categorical variable capturing the past periods Availability outlook of bank loans of a firm, where -1 indicates a deteriorated perception, 0 a neutral perception and 1 an improved perception.	-1 to 1

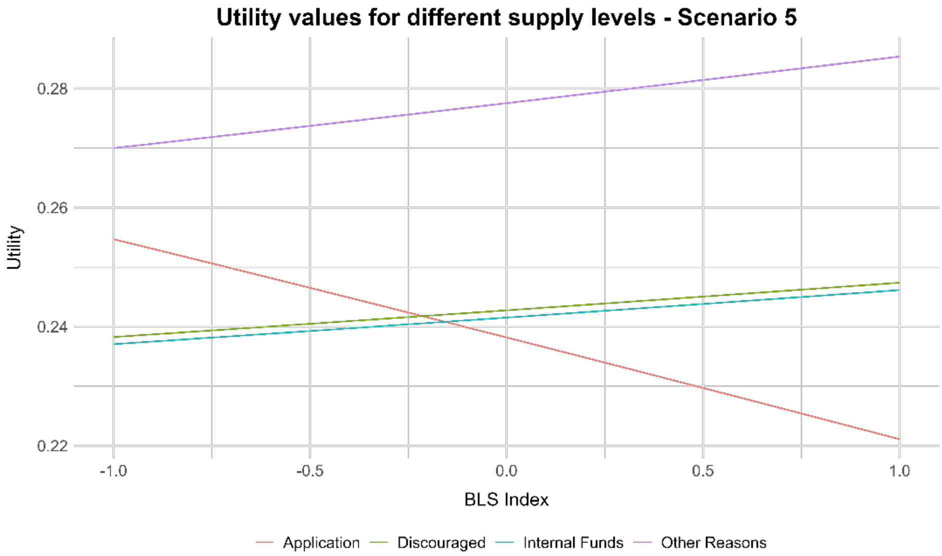
Note: This table lists the composition, measurement scale, and value range of all variables used in the empirical analysis. Firm-level characteristics (size, age, profits, investment/refinancing needs, perceptions, outlook) are drawn from the SAFE, while supply-side conditions are captured by the BLS index. Categorical variables are coded symmetrically around zero (−1, 0, 1) to maintain balanced scaling. The BLS index is standardized so that positive values indicate tighter credit standards.

Figure B1 Scenario with neutral bank loan availabilty beliefs for different firm sizes



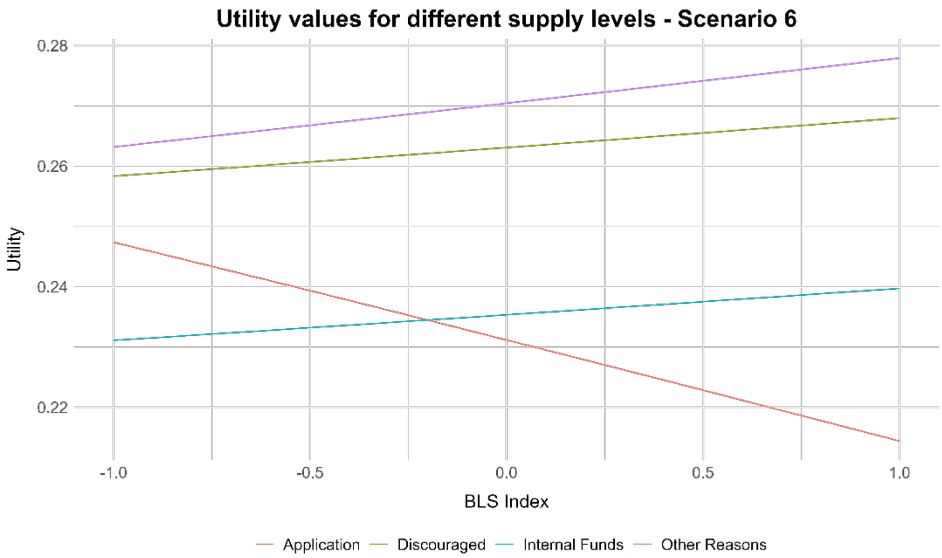
Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under neutral bank-loan-availability beliefs. Firm size varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A Firm size of 0 denotes a medium-sized firm.

Figure B2 Scenario with neutral bank loan availabilty beliefs for different supply levels



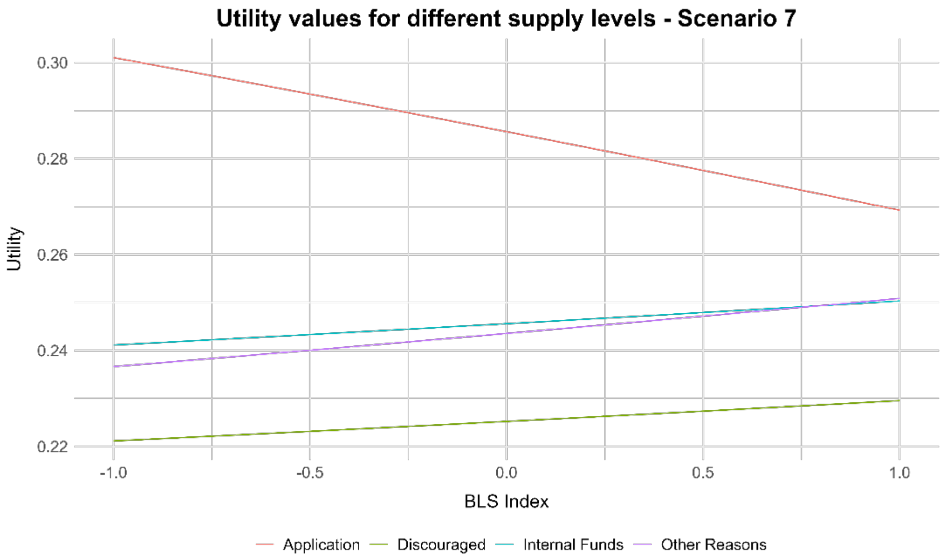
Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under neutral bank-loan-availability beliefs. BLS Index varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A positive BLS Index indicates tightened supply.

Figure B3 Scenario with post-COVID bank loan availabilty beliefs for different supply levels



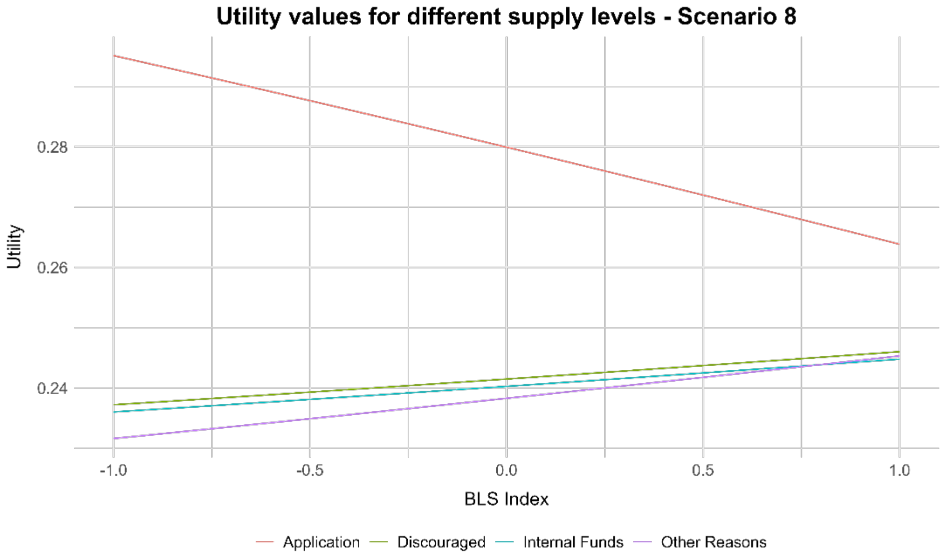
Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under pessimistic (post-Covid) bank-loan-availability beliefs. BLS Index varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A positive BLS Index indicates tightened supply.

Figure B4 Scenario with full sample loan availabilty beliefs for medium firm size and different supply levels



Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under bank-loan-availability beliefs reflecting the sample mean for a medium-sized firm. BLS Index varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A positive BLS Index indicates tightened supply.

Figure B5 Scenario with neutral bank loan availabilty beliefs for medium firm size and different supply levels



Note: The figure plots the modeled utility indices for the four behavioral outcomes, *Application (A)*, *Internal Funds (I)*, *Discouraged (D)*, and *Other Reasons (O)*, under neutral bank-loan-availability beliefs for a medium-sized firm. BLS Index varies from −1 to 1, while other covariates are held at their sample means. Indices are normalized to allow ordinal comparison across outcomes. A positive BLS Index indicates tightened supply.

Appendix C: Additional Robustness Checks and Transition Probabilities

Table C1 contains the estimation as presented in table 5 but with one-hot encoded categorical variables. This categorical coding provides us with some additional insights which confirm the mechanisms and results presented in the main body of the text. Most notably, we find that the size effects are mostly driven by small SMEs, whereas medium-sized SMEs are not significantly differing from large SMEs. Small SMEs are 7.4 – 10.5% less likely to apply than the other two size categories of firms. In contrary, for perceptions, we can see that improved and decreased perception substantially differ from the middle category. This effect is most important for discouragement, where improved perceptions lead to a 3.3 – 4.4% lower probability of discouragement, while decreased perceptions lead to a 3.5 – 5.9% higher probability of discouragement.

To further test the robustness of our findings, we split the sample into Northern and Southern euro area countries as presented in table C2 and C3. This distinction is motivated both by institutional differences and by historical developments. The North comprises countries with relatively stronger banking sectors, deeper capital markets, and lower sovereign risk premia, while the South contains countries that were more severely affected by the euro area debt crisis and the subsequent tightening of credit supply. These structural differences remain relevant for SMEs. The results confirm that our baseline mechanisms are broadly consistent across both subsamples but also reveal some differences. First, firm size matters in both groups, but the effect is particularly pronounced in the South. Second, supply-side conditions as captured by the BLS index play a stronger role in the South. While not significant in the norther sample, tighter supply shows significant effects, in some specifications, in the southern sample. There, tighter credit supply is associated a higher probability of discouragement and a lower probability of a bank loan application. Third, refinancing needs are particularly detrimental in the South, whereas in the North the coefficients are smaller and less robust. Fourth, perceptions and expectations consistently shape behavior, but their marginal effects are stronger in the South. Taken together, while the general mechanisms hold across regions, SMEs in our southern country sample are more sensitive to supply shocks, refinancing pressures, and belief-driven dynamics.

Table C1 Multinomial Logit results for the determinants of bank loan application decisions with categorical variables

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age - old	-0.003	0.022	-0.037***	0.018	-0.007	0.030	-0.034***	0.011
	(0.016)	(0.025)	(0.013)	(0.030)	(0.016)	(0.024)	(0.011)	(0.031)
Age - young	0.029	0.001	-0.011	-0.019	0.029	0.001	-0.012	-0.018
	(0.024)	(0.033)	(0.019)	(0.023)	(0.023)	(0.032)	(0.018)	(0.027)
Size - small	0.037***	-0.105***	0.028***	0.040**	0.025**	-0.074***	0.017**	0.032**
	(0.011)	(0.010)	(0.010)	(0.016)	(0.011)	(0.008)	(0.008)	(0.015)
Size large	-0.009	-0.012	-0.012	0.033	-0.015	-0.012	-0.005	0.032
	(0.014)	(0.020)	(0.023)	(0.029)	(0.014)	(0.023)	(0.020)	(0.027)
BLS Index	-0.001	0.001	0.008	-0.009	0.018*	-0.004	0.001	-0.015
	(0.014)	(0.020)	(0.006)	(0.022)	(0.011)	(0.017)	(0.006)	(0.019)
Lagged Profits	-0.029***	0.032***	-0.026**	0.023*	-0.031***	0.039***	-0.019*	0.011
	(0.006)	(0.012)	(0.011)	(0.013)	(0.006)	(0.013)	(0.010)	(0.013)
Investment	-0.040***	0.117***	-0.024***	-0.054***	-0.039***	0.097***	-0.020***	-0.037*
	(0.010)	(0.029)	(0.006)	(0.020)	(0.010)	(0.027)	(0.007)	(0.020)
Refinancing	-0.010	0.066**	0.030***	-0.087**	-0.010	0.046	0.023***	-0.059*
	(0.014)	(0.032)	(0.004)	(0.035)	(0.012)	(0.029)	(0.004)	(0.030)
Lagged improved	-0.079***	0.191***	-0.044***	-0.068***	-0.052***	0.070**	-0.033***	0.014
Perception	(0.022)	(0.027)	(0.012)	(0.025)	(0.020)	(0.028)	(0.011)	(0.025)
Lagged decreased	-0.061***	0.239***	0.059***	-0.237***	-0.043***	0.106***	0.035***	-0.098***
Perception	(0.019)	(0.035)	(0.011)	(0.024)	(0.016)	(0.033)	(0.011)	(0.025)
Lagged improved	-0.031	0.126**	-0.026*	-0.068**	-0.013	0.106**	-0.020	-0.072***
Outlook	(0.032)	(0.049)	(0.016)	(0.028)	(0.032)	(0.049)	(0.016)	(0.026)
Lagged decreased	-0.022	0.132***	-0.008	-0.103***	0.005	0.098*	-0.011	-0.092***
Outlook	(0.033)	(0.051)	(0.019)	(0.027)	(0.032)	(0.050)	(0.020)	(0.022)
Lagged Internal					-0.090***	-0.026	-0.034***	0.150***
Funds					(0.010)	(0.016)	(0.008)	(0.010)
Lagged Discouraged					-0.087***	0.079***	0.076***	-0.068***
					(0.013)	(0.024)	(0.007)	(0.023)
Lagged No Money					-0.076**	0.305***	0.041***	-0.270***
					(0.029)	(0.024)	(0.008)	(0.041)
Lagged Receive all					-0.103***	0.218***	-0.038**	-0.077***
					(0.014)	(0.013)	(0.014)	(0.013)
Lagged Receive parts					-0.087***	0.218***	0.003	-0.134***
					(0.018)	(0.019)	(0.010)	(0.019)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,333	7,333	7,333	7,333	6,891	6,891	6,891	6,891
Adjusted R^2	0.105	0.105	0.105	0.105	0.159	0.159	0.159	0.159
Log Likelihood	-8088.73	-8088.73	-8088.73	-8088.73	-7157.22	-7157.22	-7157.22	-7157.22

Note: The table presents average marginal effects from multinomial logit estimations of SMEs' bank-loan application behavior. The dependent variable includes four mutually exclusive outcomes: *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (the base category). Columns 1–4 use the baseline covariate set; columns 5–8 add lagged experience with prior loan applications. Robust standard errors are clustered at the country level and reported in parentheses. Country, wave, and sector fixed effects are included in all specifications. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation. Here, the age and size categories are one-hot encoded to ensure robustness.

Table C2 Multinomial Logit results for the determinants of bank loan application decisions for the northern EU countries

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	-0.017	0.006	-0.021***	0.032	-0.017	0.008	-0.016**	0.026
	(0.021)	(0.013)	(0.007)	(0.022)	(0.020)	(0.012)	(0.008)	(0.017)
Size	-0.016	0.096***	-0.025*	-0.054**	-0.003	0.072***	-0.016	-0.053***
	(0.015)	(0.014)	(0.013)	(0.022)	(0.014)	(0.012)	(0.011)	(0.018)
BLS Index	0.022	0.049	-0.002	-0.069	0.030	0.050	-0.002	-0.078
	(0.042)	(0.043)	(0.016)	(0.070)	(0.035)	(0.040)	(0.015)	(0.054)
Lagged Profits	-0.016**	0.015	-0.027**	0.028*	-0.022***	0.020	-0.019	0.021
	(0.007)	(0.012)	(0.012)	(0.015)	(0.006)	(0.015)	(0.012)	(0.014)
Investment	-0.059***	0.165***	-0.022**	-0.084**	-0.057***	0.135***	-0.024***	-0.054
	(0.011)	(0.043)	(0.008)	(0.037)	(0.010)	(0.041)	(0.009)	(0.035)
Refinancing	-0.020*	0.049	0.034***	-0.064	-0.015	0.021	0.023***	-0.029
	(0.012)	(0.044)	(0.005)	(0.046)	(0.012)	(0.036)	(0.005)	(0.035)
Lagged Perception	-0.013*	-0.017***	-0.053***	0.082***	-0.009	-0.005	-0.037***	0.051***
	(0.007)	(0.005)	(0.005)	(0.009)	(0.011)	(0.009)	(0.006)	(0.010)
Lagged Outlook	-0.004	-0.004	0.002	0.005	-0.007	0.002	0.005	0.000
	(0.006)	(0.006)	(0.004)	(0.007)	(0.006)	(0.007)	(0.003)	(0.009)
Lagged Internal Funds					-0.082***	-0.054***	-0.036***	0.171***
					(0.015)	(0.019)	(0.013)	(0.013)
Lagged Discouraged					-0.088***	0.060*	0.077***	-0.048
					(0.029)	(0.032)	(0.015)	(0.030)
Lagged No Money					-0.057	0.292***	0.058***	-0.292***
					(0.052)	(0.013)	(0.008)	(0.060)
Lagged Receive all					-0.094***	0.212***	-0.025**	-0.093***
					(0.023)	(0.010)	(0.012)	(0.023)
Lagged Receive parts					-0.058**	0.198***	-0.021*	-0.120***
					(0.024)	(0.022)	(0.011)	(0.039)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,736	3,736	3,736	3,736	3,496	3,496	3,496	3,496
Adjusted R²	0.078	0.078	0.078	0.078	0.141	0.141	0.141	0.141
Log Likelihood	-4203.58	-4203.58	-4203.58	-4203.58	-3677.66	-3677.66	-3677.66	-3677.66

Note: The table presents average marginal effects from multinomial logit estimations of SMEs' bank-loan application behavior. The dependent variable includes four mutually exclusive outcomes: *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (the base category). Columns 1–4 use the baseline covariate set; columns 5–8 add lagged experience with prior loan applications. Robust standard errors are clustered at the country level and reported in parentheses. Country, wave, and sector fixed effects are included in all specifications. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation. This sample split includes, AT, BE, DE, EE, FI, FR, IE, LU, LT, LV, NL and SK.

Table C3 Multinomial Logit results for the determinants of bank loan application decisions for the southern EU countries

	Other Reasons	Application	Discouraged	Internal Funds	Other Reasons	Application	Discouraged	Internal Funds
Age	-0.010	0.028	-0.017***	-0.001	-0.015	0.036	-0.019**	-0.002
	(0.019)	(0.025)	(0.007)	(0.029)	(0.016)	(0.023)	(0.008)	(0.031)
Size	-0.066***	0.133***	-0.036***	-0.031*	-0.054***	0.083***	-0.023***	-0.006
	(0.012)	(0.016)	(0.007)	(0.017)	(0.012)	(0.010)	(0.003)	(0.014)
BLS Index	-0.014	-0.020	0.010*	0.024**	0.003	-0.022**	0.005	0.015
	(0.014)	(0.024)	(0.006)	(0.012)	(0.011)	(0.010)	(0.007)	(0.010)
Lagged Profits	-0.039***	0.046**	-0.025	0.018	-0.038***	0.056**	-0.018	0.000
	(0.007)	(0.023)	(0.019)	(0.025)	(0.013)	(0.022)	(0.019)	(0.025)
Investment	-0.022**	0.081***	-0.023**	-0.036***	-0.020**	0.065***	-0.018*	-0.027*
	(0.009)	(0.015)	(0.010)	(0.009)	(0.009)	(0.016)	(0.010)	(0.014)
Refinancing	0.001	0.119***	0.025***	-0.144***	-0.002	0.090***	0.022***	-0.110***
	(0.022)	(0.032)	(0.003)	(0.022)	(0.023)	(0.029)	(0.007)	(0.025)
Lagged Perception	-0.002	-0.029**	-0.050***	0.080***	0.001	-0.029***	-0.030**	0.058***
	(0.005)	(0.015)	(0.014)	(0.004)	(0.004)	(0.010)	(0.012)	(0.009)
Lagged Outlook	-0.009	-0.002	-0.019***	0.031***	-0.013**	0.007	-0.014***	0.020***
	(0.006)	(0.012)	(0.004)	(0.006)	(0.005)	(0.008)	(0.004)	(0.003)
Lagged Internal Funds					-0.096***	0.005	-0.025***	0.116***
					(0.014)	(0.026)	(0.007)	(0.008)
Lagged Discouraged					-0.091***	0.135***	0.074***	-0.117***
					(0.006)	(0.040)	(0.008)	(0.036)
Lagged No Money					-0.104***	0.368***	0.026***	-0.289***
					(0.018)	(0.073)	(0.010)	(0.078)
Lagged Receive all					-0.116***	0.265***	-0.052*	-0.096***
					(0.019)	(0.030)	(0.031)	(0.014)
Lagged Receive parts					-0.119***	0.276***	0.017	-0.174***
					(0.026)	(0.036)	(0.011)	(0.015)
Country, wave & sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,597	3,597	3,597	3,597	3,395	3,395	3,395	3,395
Adjusted R^2	0.121	0.121	0.121	0.121	0.183	0.183	0.183	0.183
Log Likelihood	-3897.37	-3897.37	-3897.37	-3897.37	-3422.01	-3422.01	-3422.01	-3422.01

Note: The table presents average marginal effects from multinomial logit estimations of SMEs' bank-loan application behavior. The dependent variable includes four mutually exclusive outcomes: *Application*, *Discouraged*, *Internal Funds*, and *Other Reasons* (the base category). Columns 1–4 use the baseline covariate set; columns 5–8 add lagged experience with prior loan applications. Robust standard errors are clustered at the country level and reported in parentheses. Country, wave, and sector fixed effects are included in all specifications. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Although coefficients for *Other Reasons* are omitted in the regression output, predicted probabilities are functions of the estimated parameters for the other outcomes. Marginal effects are computed using Stata 18's *mlogit* command and *margins* postestimation. This sample split includes, CY, ES, GR, IT, MT, PT and SI.

One further step to ensure robustness and to examine changing bank loan application behaviors over time is to calculate the transition probabilities from one application state to another. These probabilities, derived from the panel structure of our data, provide the foundation for estimating a COVID shock scenario and a subsequent "new normal". The calculated transition probabilities are presented in Table C4.

Table C4 Transition probabilities

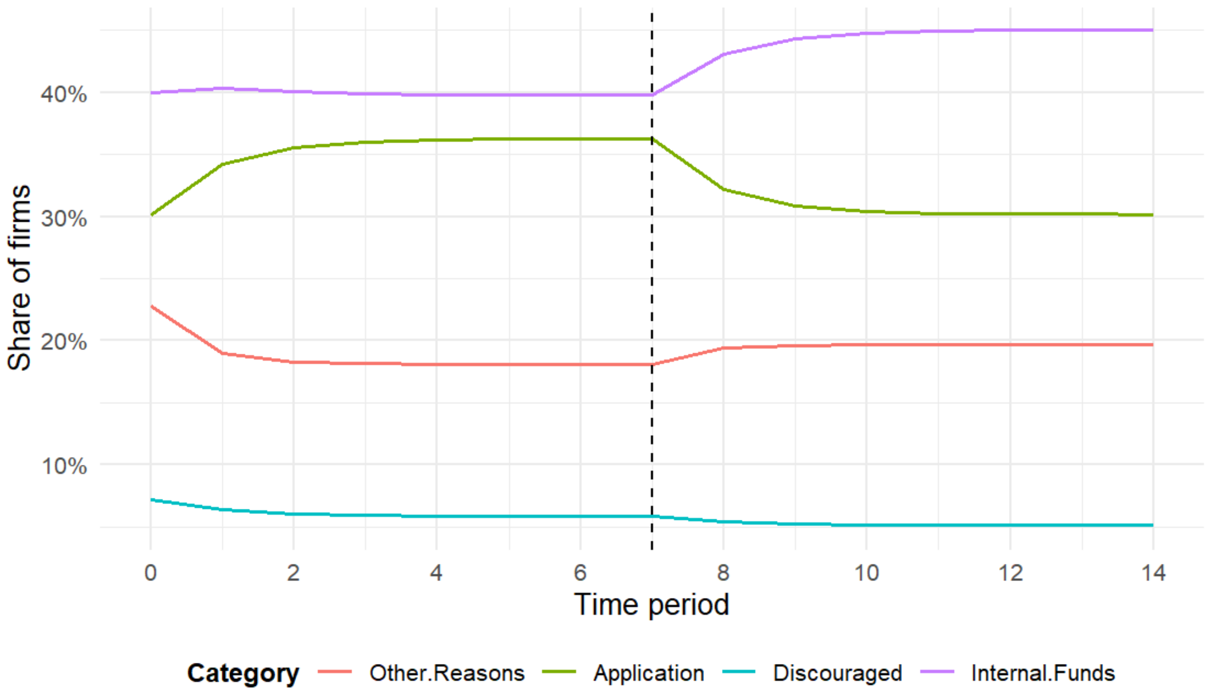
Pre-COVID				
Other Reasons	0.309	0.269	0.062	0.360
Application	0.139	0.588	0.044	0.229
Discouraged	0.190	0.237	0.401	0.172
Internal Funds	0.160	0.218	0.020	0.602

Post-COVID				
Other Reasons	0.327	0.228	0.061	0.384
Application	0.155	0.521	0.042	0.282
Discouraged	0.211	0.259	0.333	0.197
Internal Funds	0.166	0.192	0.021	0.621

Notes: The transition probabilities are calculated based on all waves in our sample, i.e. wave 11 to wave 34. The transition probabilities are calculated based on the pre-COVID (H1 2014 to H2 2019) and post-COVID (H2 2022 to H1 2025) subsample excluding the COVID period (H1 2020 to H1 2022).

Investigating the transition probabilities, a substantial percentage of firms that remain in the state they started off, can be noticed. This confirms our expectation of stickiness in firms' behavior. We simulate now 14 periods with a shift in period 7 marking the transition from the pre-COVID transition probabilities to the post-COVID transition probabilities. The result is presented in Figure C1. Noticeable, the share of firms applying is substantially decreasing considering the new normal after COVID, while the shares of firms relying on internal funds and not applying for other reasons are increasing. Discouragement experiences a slight decline, staying mostly stable.

Figure C1 COVID shock and new normal



Note: This figure shows the simulated evolution of SMEs' bank-loan-application behavior over 14 periods. The vertical dashed line marks the transition from the pre-COVID to the post-COVID regime (period 7). Transition probabilities are taken from Table C4, calculated separately for the pre-COVID (H2 2014–H2 2019) and post-COVID (H2 2022–H1 2025) subsamples, excluding the COVID period (H1 2020–H1 2022). Shares represent the equilibrium distribution of firms across four categories—*Application*, *Discouraged*, *Internal Funds*, and *Other Reasons*—in each period. The results illustrate a persistent decline in the share of firms applying for bank loans after COVID and an increase in reliance on internal funds and non-application for other reasons.

We know that small firms are especially affected by information asymmetries and thus lending constraints. Therefore, we repeat this exercise only for small firms as presented in table C5 and figure C2.

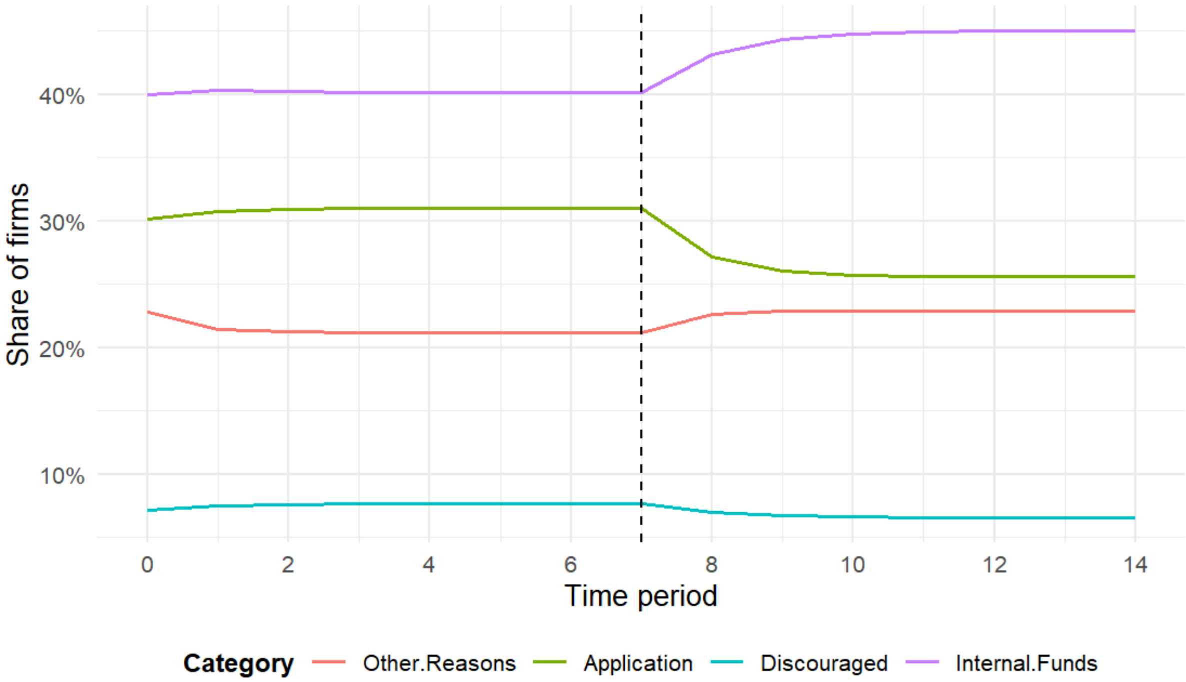
Table C5 Transition probabilities for small firms

Pre-COVID				
Other Reasons	0.332	0.240	0.070	0.358
Application	0.170	0.528	0.063	0.239
Discouraged	0.196	0.211	0.436	0.157
Internal Funds	0.184	0.198	0.022	0.596
Post-COVID				
Pre Covid	0.348	0.204	0.067	0.381
Other Reasons	0.193	0.456	0.061	0.291
Application	0.218	0.246	0.347	0.189
Discouraged	0.190	0.170	0.026	0.614

Notes: As in Table C4, but here calculated only for the small firms' category.

As can be seen, the results are even more pronounced for this category of firms. The equilibrium suggests that only one quarter of small firms applies for a bank loan, while, notably, a similar share does not apply because of other reasons, i.e. presumably infavorable costs and borrowing terms.

Figure C2 COVID shock and new normal for small firms



Note: The figure replicates the simulation from Figure C1, restricted to small firms (fewer than 50 employees). Transition probabilities are based on Table C5, using pre-COVID (H2 2014–H2 2019) and post-COVID (H2 2022–H1 2025) transition matrices. The simulation highlights that the reduction in loan applications is particularly pronounced among small firms, with equilibrium behavior indicating stronger reliance on internal funding and a higher share of non-applicants for other reasons.