Bank Specialization and Corporate Innovation

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Abstract

Theory offers conflicting predictions on how bank specialization affects corporate innovation. We show that the sign and magnitude of this effect vary with the degree of "asset overhang" across sectors—the risk that new technologies reduce the value of banks' legacy loan portfolios. Using Belgian innovation survey data and U.S. patent data, we find that lenders' sectoral specialization enhances innovation for firms operating in sectors with low asset overhang, but hinders innovation in sectors with high asset overhang. These findings are robust to different measures of asset overhang and an identification strategy using bank mergers. We further show that these heterogeneous effects arise through financial contracting. Our findings highlight how product market characteristics shape the role of bank specialization in innovation.

Keywords: Bank specialization, Bank lending, Corporate innovation, Asset overhang, Financial frictions

JEL Classification: G20, O30, L20

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1. Introduction

Prior research has identified various channels through which the banking sector affects corporate innovation. Bank competition and lending relationships generally enhance firms' innovation activities (Cornaggia et al. 2015; Herrera and Minetti 2007), whereas zombie lending negatively impacts innovation (Schmidt et al. 2023). Despite this growing body of work, the role of bank specialization—i.e., the extent to which banks concentrate lending in specific sectors (Blickle, Parlatore, and Saunders 2024; Paravisini, Rappoport, and Schnabl 2023)—remains largely unexplored. Given that bank specialization is a key feature of banks' business models, and theory offers ambiguous predictions about its effect on corporate innovation, addressing this research gap is particularly important.

On the one hand, specialized banks may develop sector-specific expertise, enhancing their screening and monitoring capabilities (Blickle, Parlatore, and Saunders 2024; Blickle et al. 2025) for financing risky and opaque innovation projects (Hall and Lerner 2010; Rajan and Zingales 2001). On the other hand, specialized banks face heightened exposure to negative spillovers arising from innovation—such as business stealing and collateral devaluation (e.g., Aghion and Howitt 1992; Bloom, Schankerman, and Van Reenen 2013)—potentially reducing their incentives to finance innovation. Thus, the overall effect of bank specialization on innovation remains an open empirical question.

To address this question, we use two unique and complementary datasets. The first one merges the Community Innovation Survey (CIS) with Belgian credit register data, capturing all potential forms of innovation (including non-patented product and process innovations). It covers many small, bank-dependent firms that face large switching costs and have limited access to other types of financing (such as private equity or venture capital). The second one combines U.S. syndicated loan data with patent data, covering larger, often publicly listed firms. Although the U.S. data sample is limited to specific types of innovation output (i.e., patents) and firms (i.e., large, typically listed firms), it enables sharper identification using bank mergers as an exogenous source of variation in bank specialization and enhances the external validity of our analysis. The two datasets thus allow testing our hypotheses across different innovation types and institutional settings.

Using these datasets, we assess how bank specialization, measured by the proportion of a bank's loan portfolio allocated to a particular sector, affects various innovation outcomes: product, process, and world-first innovations in Belgium, and patent quantity and quality in the U.S.

Our key finding is that bank specialization's impact on innovation critically depends on asset overhang, which corresponds to the risk that new technologies depreciate the value of banks' existing loans (Degryse, Roukny, and Tielens 2024).[1] Specifically, specialization boosts innovation in sectors with low asset overhang but impedes it in sectors with high asset overhang. This finding is robust across multiple measures of asset overhang and consistent across datasets, highlighting how product market characteristics can act as financial frictions that restrict banks' potential to spur corporate innovation.

Building on prior research, we construct three measures of asset overhang. For the Belgian data, we employ capital intensity, as firms in highly capital-intensive sectors typically have large upfront investments, making them more vulnerable to technological devaluation effects (Gulen and Ion 2016). For the U.S. data, we use asset redeployability (Kim and Kung 2017) and product market rivalry (Bloom, Schankerman, and Van Reenen 2013). Capital intensity and asset redeployability primarily capture how new technologies affect the value of pledged collateral, while product market rivalry measures the extent to which firm value is affected via business stealing, covering the two primary externalities from technological change (Aghion and Howitt 1992).

We incorporate these measures by interacting them with lenders' sectoral specialization in our baseline regressions. We find that the sign and magnitude of the effect of bank specialization on innovation vary with asset overhang. Specifically, in sectors with low asset overhang, specialized banks positively impact innovation, whereas in sectors with high asset overhang, their impact is negative. These results are consistent, significant, and economically meaningful across both datasets. For instance, in the Belgian sample, a one standard deviation increase in lenders' sectoral specialization increases (decreases) the probability of introducing product innovations and world-first innovations by 10% and 35%, respectively.

[1] Note that the asset overhang problem proposed by Degryse, Roukny, and Tielens (2024) differs from the debt overhang problem put forward by Myers (1977) as the latter refers to how a firm's outstanding debt may adversely affect its investment incentives.

In the U.S. sample, the equivalent increase in specialization is associated with a 10–15% increase (decrease) in patents and patent citations for firms in sectors with low (high) asset overhang. In the U.S. sample, these effects are particularly pronounced among the more bank-dependent firms borrowing in the syndicated loan market.

We validate our results with several robustness checks. First, to address potential endogeneity concerns regarding lenders' sectoral specialization, we leverage exogenous variation from mergers between U.S. banks active in the syndicated loan market, following Iyer et al. (2022) and Saidi and Streitz (2021). We further confirm the absence of endogenous matching between innovative firms and specialized banks across sectors with varying asset overhang, using the approach of Foà et al. (2019).

Second, we rule out alternative explanations. One possible alternative mechanism is zombie lending, as bank specialization has been shown to reduce zombie lending (De Jonghe, Mulier, and Samarin 2025) which could in turn enhance innovation (Schmidt et al. 2023). Another possibility is technological conservatism, whereby banks hinder corporate innovation due to reluctance to learn about new technologies (Minetti 2011). We show that these alternative channels do not drive our findings.

Third, we address omitted variable concerns by demonstrating that interactions between asset overhang and other bank characteristics—such as market share and competition—are statistically insignificant, reinforcing the relevance of our identified channel.

Fourth, focusing on the U.S. sample, we show that our results also hold when we focus on the novelty of firms' patents. Radical innovations, characterized by higher patent originality and generality, are riskier and more impactful than incremental innovations (Trajtenberg, Henderson, and Jaffe 1997). Consistent with our main findings, bank specialization positively influences patent novelty in low-overhang sectors and negatively in high-overhang sectors—an important result given radical innovation's role in driving long-term economic growth (Acemoglu 2008). Moreover, our results reflect intensive rather than extensive margins of patenting; bank specialization impacts patent quality and quantity among active innovators but does not affect patent entry or exit, regardless of the underlying asset overhang.

Finally, we confirm robustness through alternative empirical specifications, sub-samples,

and measurement approaches, including varying definitions of bank specialization and different fixed effect structures.

Our analysis shows that bank specialization has heterogeneous effects on corporate innovation, stemming from sectoral differences in asset overhang. Based on prior literature, we posit financing conditions as the primary mechanism through which banks influence firms' investments in innovative projects (Amore, Schneider, and Žaldokas 2013; Granja and Moreira 2023; Herrera and Minetti 2007). We thus focus on banks' traditional role as financiers. Using the Belgian Community Innovation Survey (CIS), we first examine whether access to external finance poses a significant barrier to innovation. Consistent with bank lending mechanisms, we find firms borrowing from specialized banks in sectors with low (high) asset overhang are around 10 percentage points less (more) likely to report financing constraints.

Next, using loan level data from the Belgian credit register and U.S. syndicated loans, we study how bank specialization impacts borrowers' loan conditions depending on sector innovativeness and asset overhang. We examine loan amounts, rates, maturities, collateral requirements, and covenants—key factors influencing innovative investments. Loan maturities, for instance, influence firms' refinancing risks and incentives for long-term investments (Aghion et al. 2010; Diamond 1991, 1993; Johnson 2003), while covenants affect firms' flexibility to undertake risky projects (Chava and Roberts 2008; Nini, Smith, and Sufi 2009).

We find that specialized banks offer significantly worse loan conditions to firms in innovative, high-overhang sectors, including higher rates and stricter collateral requirements, reflecting compensation for technological spillovers. Additionally, these firms face shorter maturities and tighter covenants, constraining investments in long-term projects. For example, a one standard deviation increase in bank specialization reduces firms' covenant strictness by 6% on average; however, for firms in innovative, high asset overhang sectors, it increases strictness by 10%. These results indicate banks internalize potential negative spillovers of innovation on their legacy loan portfolios, directly influencing firms' financing and innovation activities.

Related Literature Our paper contributes to several strands of literature. First, we add to the extensive literature on finance and innovation (for an overview, see Hall and Lerner 2010; Kerr and Nanda 2015). Despite the importance of venture capital for innovative

firms, there is increasing evidence that bank credit also significantly supports innovation (e.g., Hochberg, Serrano, and Ziedonis 2018; Kerr and Nanda 2015; Robb and Robinson 2014). Several studies examine how improved access to bank credit and credit supply shocks affect innovation. Others focus on lending relationships (Herrera and Minetti 2007; Hombert and Matray 2017) or banks' zombie lending (i.e., lending to non-viable firms that would otherwise exit, see Schmidt et al. 2023). We extend this literature by analyzing how bank specialization affects corporate innovation and economic growth.

Second, our study contributes to research on the interaction between financial and product markets (for an overview, see Frésard and Phillips 2024). Specifically, we relate to papers examining financial frictions that shape banks' incentives to finance innovation (Atanassov 2016; Araujo et al. 2019; Cerqueiro et al. 2017; Degryse, Roukny, and Tielens 2024; Minetti 2011; Saidi and Žaldokas 2021). We demonstrate that banks' business models interact with product market features, such as asset redeployability or product market rivalry, influencing their decisions to finance innovation. More broadly, our findings complement recent studies by López and Vives (2019) and Antón et al. (2025), who show that common ownership can positively or negatively impact innovation depending on the strength of technological and market spillovers. Our study extends these insights to the context of bank specialization.

Finally, our paper relates to a nascent literature on bank specialization. Recent evidence highlights that banks specialize by focusing their lending in specific sectors (Blickle, Parlatore, and Saunders 2024).[2] Such specialization enables banks to develop expertise, reducing screening and monitoring costs (Blickle et al. 2025) and facilitating more favorable loan conditions (Blickle, Parlatore, and Saunders 2024; Cao et al. 2023; Giometti, Güler, and Pietrosanti 2022). Additionally, De Jonghe, Mulier, and Samarin (2025) find that specialization reduces zombie lending, as specialized banks are better informed about zombie firms and related negative spillovers on healthy firms. Further emphasizing spillover effects, Iyer et al. (2022) and Paravisini, Rappoport, and Schnabl (2023) show that bank specialization significantly influences the propagation of shocks to the real economy. We contribute by studying how specialization influences corporate innovation, uncovering that it is beneficial in sectors with

[2]While we focus on sectoral specialization, there is growing research on geographic specialization (Casado and Martinez-Miera 2023; Doerr and Schaz 2021; Duquerroy et al. 2022).

low asset overhang but detrimental in sectors with high asset overhang.

2. Theoretical Background

In this section, we outline theoretical predictions about how bank specialization affects firms' innovation output. Bank specialization could positively affect innovation by enabling banks to develop sector-specific expertise, improving their screening and monitoring abilities (Blickle, Parlatore, and Saunders 2024; Blickle et al. 2025). Since innovation often involves investments in opaque and risky assets (Hall and Lerner 2010; Herrera and Minetti 2007; Rajan and Zingales 2001), specialized banks may be better positioned to support innovative projects. Formally, our first hypothesis (H1) is:

H1: Bank specialization has a positive effect on firms' innovation output.

However, this positive effect could be reduced by technological spillovers, particularly relevant for specialized banks. The Schumpeterian concept of "creative destruction" highlights how new technologies can render existing products, markets, and manufacturing processes obsolete via business stealing or collateral devaluation (Aghion and Howitt 1992, 1998; Aghion, Akcigit, and Howitt 2015; Schumpeter 1943).[3] In line with this idea, Bloom, Schankerman, and Van Reenen (2013) show that, for firms that operate closely in product market space, the innovation activities of one firm can reduce the market value of other firms. In a similar vein, Kogan et al. (2017) show that the innovation activities of a firm's competitors can have a negative effect on a firm's growth prospects by increasing the obsolescence risk of its products and processes and the loss of market share (also see Ma 2025; Utterback 1994).

Expanding on these ideas, Degryse, Roukny, and Tielens (2024) extend the model by Holmstrom and Tirole (1997) to study how technology-driven spillovers influence banks' funding incentives. They argue that banks might avoid financing innovative projects that risk devaluing their legacy loan portfolios, a phenomenon they term "asset overhang" (also see Becker and Ivashina 2023). Such effects are especially pronounced for specialized banks, whose

[3]Kodak is a good example of a firm whose product became obsolete due to technological change. In the 1980s and 1990s, Kodak was the leading producer of films for cameras and one of the most active patenting firms in the U.S. However, after 1996, the diffusion of digital photography caused a collapse in the demand for physical film, which pushed Kodak into a period of dramatic decline. In essence, Kodak experienced a large negative shock caused by a new technology that made its main product obsolete. Consequently, between 1996 and 2007, as the market for digital photography grew and the market for physical films shrank, Kodak's stock price declined by more than 80% (Moretti 2021).

portfolios concentrate disproportionately in specific sectors, heightening their vulnerability to sector-specific technological shocks. Hence, banks' incentive to impede innovation increases with their level of sectoral specialization. Importantly, this incentive only applies if new technologies negatively affect existing ones, which is not always the case. While innovations can negatively impact firms competing closely in product markets, they may also generate positive spillovers for firms closely positioned in technology space (Bernstein and Nadiri 1989; Bloom, Schankerman, and Van Reenen 2013; Jaffe 1986; Kogan et al. 2017). Generally, negative spillovers from innovation occur through two channels; (1) reductions in firm value from decreased collateral value, and (2) reductions due to diminished performance (e.g., through business stealing) (Aghion and Howitt 1992; Becker and Ivashina 2023; Bloom, Schankerman, and Van Reenen 2013). Following Degryse, Roukny, and Tielens (2024), we label the underlying risk as asset overhang, and formulate our second hypothesis (H2) as follows:

H2: Bank specialization positively affects firms' innovation output in sectors with low asset overhang but negatively affects it in sectors with high asset overhang.

3. Data and Measurement

This section first defines the construction of the key variables, namely bank specialization, asset overhang, and corporate innovation. Subsequently, we describe the various data sources, merging of data, and summary statistics.

3.1 Measuring Bank Specialization

We construct our main independent variable at the bank-sector-year level, using 2-digit NACE sectors. Following prior literature (e.g., De Jonghe, Mulier, and Samarin 2025; Iyer et al. 2022; Blickle, Parlatore, and Saunders 2024), we define a bank's sectoral specialization as the share of its total credit allocated to a given sector:

$$Bank\ specialization_{b,s,t} = \frac{\sum_{f=1}^{F^s} Credit_{b,f,s,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F^s} Credit_{b,f,s,t}} \tag{1}$$

where $Credit_{b,f,s,t}$ denotes the credit from bank b to firm f in sector s at time t, F^s is the number of firms in sector s, and S is the total number of sectors. This measure ranges from zero (no lending to the sector) to one (full specialization), capturing the sector's weight in the bank's loan portfolio. In robustness checks, we confirm that our results hold using alternative definitions of specialization, including measures based on 3-digit industry codes and on the number of lending relationships rather than credit volume.[4]

3.2 Measuring Asset Overhang

We construct three measures of asset overhang capturing the risk that new technologies negatively impact the value of banks' legacy loan portfolios. Specifically, we focus on two main channels; (1) collateral devaluation, and (2) reduced firm performance through business stealing (Aghion and Howitt 1992; Bloom, Schankerman, and Van Reenen 2013; Schumpeter 1943; Utterback 1994).

First, for the Belgian sample, we measure capital intensity as the sector level average ratio of firms' fixed assets to total assets. Firms in highly capital-intensive sectors typically invest in specialized physical assets requiring large upfront costs (Gulen and Ion 2016), increasing their vulnerability to technological obsolescence and asset devaluation.[5] We acknowledge capital intensity is a rough proxy as it omits factors like asset specificity or mobility, which we capture using more granular measures available for the U.S. sample.

Second, for the U.S. sample, we adopt the asset redeployability measure from Kim and Kung (2017), based on the 1997 Bureau of Economic Analysis capital flows data, containing capital expenditures for 123 sectors across 180 asset categories. Kim and Kung (2017) first compute asset level redeployability scores, defined as the proportion of sectors utilizing each asset, thus capturing asset redeployability both *within* and *across* sectors.[6] Sector-year level scores are then derived as weighted averages of these asset-level scores, based on each asset's share of sector capital expenditures. Assets with higher redeployability have lower collateral

[4]The Belgian credit register captures nearly all lending relationships, as banks must report exposures exceeding €25,000. The U.S. syndicated loan data covers only a subset of banks' entire loan portfolio. To address potential measurement error, robustness checks show our results are unchanged when excluding bank-sector-time bins with fewer than ten loan facilities.

[5]Additionally, these firms face higher adjustment costs when adopting new technologies.

[6]The computed asset-level redeployability scores seem reasonable (see Kim and Kung 2017); for example, the score is 0.66 for "industrial trucks, trailers, and stackers," which are used in a wide range of sectors, while the score is 0.02 for "drilling oil and gas wells," which are almost exclusively used in the oil and gas sectors.

devaluation risk (Benmelech 2009; Benmelech and Bergman 2009), implying lower asset overhang.

Third, for the U.S. sample, we also utilize the product market rivalry measure introduced by Bloom, Schankerman, and Van Reenen (2013). This measure aggregates rival firms' R&D stocks based on pairwise proximity in product market space, determined by the sectoral distribution of firms' sales. The microeconomic foundations are described in detail by Bloom, Schankerman, and Van Reenen (2013), but in essence the measure captures firms' exposure to innovation-driven competition. Firms in sectors with higher product market rivalry face greater risks of losing market share due to rivals' innovations (Aghion and Howitt 1992; Antón et al. 2025; Becker and Ivashina 2023), indicating higher asset overhang.

For comparability, we standardize all measures to have a mean of zero and standard deviation of one, ensuring negative (positive) values correspond to low (high) asset overhang sectors.[7]

3.3 Measuring Innovation

For Belgian companies, we use innovation indicators from the Community Innovation Survey (CIS). The CIS is Europe's primary instrument for collecting firm level innovation data, conducted biannually by national statistical offices following EU-wide definitions outlined in the Oslo Manual.[8] The survey gathers information on firms' product and process innovations, innovation strategies, and factors influencing innovation.[9] We use Belgian CIS data from six survey waves between 2008 and 2020, focusing on three key questions. First, we construct two binary variables indicating whether a firm introduced a product or process innovation. Product innovation captures new or significantly improved goods or services; process innovation captures new or significantly improved production or logistical methods. We also create a third binary variable indicating world-first innovations, capturing innovations that are new to the entire world. This allows capturing both the quantity and novelty of firms' innovation output. The CIS offers two advantages. First, it measures all types of innovation, including

[7] For consistency, we transform the asset redeployability measure into an asset irredeployability measure.

[8] See https://www.oecd.org/en/publications/2005/11/oslo-manual_g1gh5dba.html.

[9] The CIS informs the European Innovation Scoreboard and academic research. Recent studies in the field of banking and innovation using CIS or similar surveys include Schmidt et al. (2023) for Europe, Nanda and Nicholas (2014) for the U.S., Benfratello, Schiantarelli, and Sembenelli (2008) for Italy, and Bircan and De Haas (2020) for Russia.

non-patented ones, thus mitigating concerns about the patent-secrecy trade-off in bank lending (Saidi and Žaldokas 2021). Second, it covers all firm types, including small, private firms heavily dependent on bank financing and lacking access to alternative funding sources like private equity or venture capital.[10]

We measure innovation by U.S. firms using patent data from PATSTAT, the largest international patent database with detailed information on patent records, application dates, citations, and technology classes. Following the innovation literature, we capture innovation through the quantity and quality of firms' patents (e.g., Chava et al. 2013; Nanda and Nicholas 2014).[11] Patent quantity is measured as the number of patents filed (and later granted) by firm f in year t. We use application year, rather than grant year, of patents as it better reflects the timing of invention (Hall, Jaffe, and Trajtenberg 2001). Patent quality is measured as the average number of forward citations a firm's patents receive from subsequent applications. Highly cited patents are typically viewed as having greater scientific and economic impact.[12] Consistent with prior work, we count citations received within five years after a patent is granted. Descriptive statistics for our two patent variables are reported in Table O4 in the Online Appendix and align with patterns in Hall, Jaffe, and Trajtenberg (2001).[13]

3.4 Data Sources

Our main analysis uses Belgian data. We match the Community Innovation Survey data (administered by the Belgian Science Policy Office) with credit register and financial statement data (both from the National Bank of Belgium) using VAT identification numbers. This merge results in a firm-bank-year dataset, which records innovation and financial variables for each firm-bank pair and the sectoral specialization of each lending bank. We then aggregate

[10]The CIS targets firms with ten or more employees operating in sectors with two-digit NACE codes 05-39, 46, 49-53, 58-66, and 71-73. Stratified random sampling based on firms' economic activity, size, and region ensures representativeness.

[11]Patents offer several advantages over R&D expenditures as innovation measures (Atanassov 2016). First, R&D reflects input, while patents capture output. Second, patents allow assessment of quality and novelty of innovation. Third, patents are not sensitive to accounting treatments (e.g., capitalization vs. expensing). As a result, patents are widely accepted for measuring technological change.

[12]Intuitively, the rationale is that firms that build on a previous patent have to cite that patent, which implies that the patent that is cited is technologically and economically influential. In line with this idea, Hall, Jaffe, and Trajtenberg (2005) for instance show that there is a positive relationship between patent citations and firm value (also see Kogan et al. 2017).

[13]Our results are robust to using a seven-year citation window to address truncation bias. They also remain robust to adjusting patent and citation count by technology class-year, following Hall, Jaffe, and Trajtenberg (2001) and Lerner and Seru (2022), to account for fluctuations in technological trends.

this data to the firm-year level. For firms borrowing from multiple banks, we compute the weighted average of bank specialization, using each bank's share of total firm loan exposure. Since most Belgian firms borrow from a single bank (Degryse et al. 2019), this aggregation affects only a small fraction of firms. We exclude utilities and financial firms. The final dataset comprises 7,704 non-financial firms participating in CIS surveys conducted between 2008 and 2020.[14] These firms operate across 64 distinct (2-digit NACE) sectors and borrow from 29 unique banks. Table A1 in the Appendix provides detailed variable definitions.

Our U.S. analysis relies on three main data sources. First, we obtain syndicated loan data from LPC DealScan, commonly used to examine how bank lending policies affect the real economy (Ivashina and Scharfstein 2010; Saidi and Streitz 2021). These data include detailed loan terms (loan amounts, pricing, maturities, covenants), lender information, and borrower details. Although loan syndicates involve multiple lenders (lead arrangers and participants), following prior literature (e.g., Chakraborty, Goldstein, and MacKinlay 2018), we attribute the full loan amount to lead arrangers, as they typically handle borrower screening and monitoring (Ivashina 2009; Sufi 2007).[15] Our main analysis identifies lead arrangers following Chakraborty, Goldstein, and MacKinlay (2018), but we provide robustness tests using the procedure from Ivashina (2009). Second, we obtain annual firm financial data from Compustat, including balance sheet items (total assets, total debt), profit-and-loss accounts (including R&D expenses), and general information (industry classification, state of incorporation). Third, we retrieve patent data from PATSTAT, as explained earlier. We merge these datasets into a firm-year dataset containing innovation output, financial statements, asset overhang, and banks' sectoral specialization. Merging details are in Online Appendix O.B. The final U.S. dataset comprises 5,504 firms operating in 58 (2-digit SIC) sectors from 1996 to 2013.[16] These firms borrow from 131 unique banks active in the syndicated loan market.

It should be emphasized that the U.S. data offer two key advantages compared to the Belgian data. First, the U.S. data enable constructing more granular asset overhang measures (see Section 3.2). Second, the U.S. data allow important robustness tests addressing

[14] Lenders' sectoral specialization is measured using the entire credit register.

[15] We exclude term loans B, which banks typically sell on the secondary market after syndication (Blickle et al. 2020). In robustness checks, we confirm our results hold if we instead use lead arrangers' actual loan shares to calculate bank specialization.

[16] The sample ends in 2013 due to the linking table from Arora, Belenzon, and Sheer (2021) and citation computation constraints (tracking citations 5–7 years post-grant, with a 1–3-year patent approval period).

endogeneity concerns that are not possible with the Belgian data (see Section 5). Table O1 in the Online Appendix briefly compares key characteristics and strengths of the Belgian and U.S. datasets.

3.5 Summary Statistics

Panels (a) and (b) of Figure 1 show the distribution of banks' sectoral specialization in the Belgian and U.S. data, respectively. In both cases, while loans to a particular sector typically account for less than 5% of a bank's portfolio, there are cases where one sector exceeds 30%. This indicates that banks often concentrate lending in a few sectors. Blickle, Parlatore, and Saunders (2024) and De Jonghe, Mulier, and Samarin (2025) provide further evidence that in both the U.S. and Belgium, most sectors have at least one specialized bank, and most banks specialize in at least one sector. Bank specialization is thus a key feature of banks' lending practices and business models.

Panels (a) and (b) of Figure 2 display heat maps of asset overhang across sectors using our three measures. Panel (a) uses capital intensity (Belgian data, 2-digit NACE codes), while Panel (b) uses asset redeployability and product market rivalry (U.S. data, 2-digit SIC codes). Each map shows the average (standardized) asset overhang for each sector over the sample period. Brighter (yellow) colors indicate higher asset overhang; darker (purple) colors indicate lower values. The patterns are intuitive. For instance, the Rental and Leasing sector (NACE 77) and Restaurant sector (NACE 55) have high capital intensity. Textile Mill Products (SIC 22) and Railroad Transportation (SIC 40) have high asset overhang due to the low redeployability of sector-specific assets like cotton yarn mills and locomotives. The Electrical Equipment sector (SIC 36) shows high product market rivalry, consistent with anecdotal evidence from semiconductor manufacturing.[17]

Table 1 reports descriptive statistics for our main sample of Belgian firms, while Table 2 compares key characteristics of firms with and without product or process innovations. The results indicate that innovative firms tend to be larger, invest more in R&D, have fewer fixed assets, and operate in slightly more concentrated industries. They also maintain

[17] See Forbes (2023), "The microchip war requires strategic innovation to win." https://www.forbes.com/sites/forbestechcouncil/2023/02/15/the-microchip-war-requires-strategic-innovation-to-win/?sh=49aa6db2749f.

slightly longer lending relationships but borrow from banks with similar sectoral specialization (around 5% on average). Table O2 in the Online Appendix provides summary statistics for the U.S. sample, and Table O3 compares patenting and non-patenting U.S. firms. Overall, the patterns align with patterns described by Atanassov (2013, 2016), among others. As discussed in our empirical approach below, we control for a large set of control variables in all our regression models to mitigate potential concerns about omitted variable bias. Finally, Tables O5 and O6 in the Online Appendix show pairwise correlations among key independent variables for the Belgian and U.S. samples, indicating little evidence of collinearity.

4. Results

The results section is structured as follows. We first examine the effect of bank specialization on the different dimensions of firms' innovation output using the Belgian credit register data combined with innovation survey data. We then extend our analysis using U.S. syndicated loan data merged with patent data. Finally, we investigate the underlying mechanism through which bank specialization influences corporate innovation.

4.1 Main Results: Evidence from Belgium

We start by testing Hypothesis 1, which posits that bank specialization has a positive effect on firms' innovation output, using the following regression model:

$$y_{f,b,s,t} = \beta Bank\ specialization_{b,s,t-1} + \gamma C_{f,b,s,t-1} + \lambda_{s,t} + \lambda_{l,t} + \epsilon_{f,b,s,t} \quad (2)$$

where f, b, s, and t refer to firm, bank, sector, and time, respectively. The outcome variable $y_{f,b,s,t}$ represents different outcomes for firm innovation.[18] $Bank\ specialization_{b,s,t-1}$ is the lagged sectoral specialization of a firm's lender. For firms with more than one lender, this variable equals the weighted sectoral specialization of the firm's lenders. $C_{f,b,s,t-1}$ is a vector of lagged control variables.[19] $\lambda_{s,t}$ and $\lambda_{l,t}$ are sector-by-time and locality-by-time fixed effects,

[18]The outcome variable varies at the firm-year level. We add the bank and sector indication to indicate the level of variation that we aim to explain with the independent variables of interest.

[19]The vector of lagged control variables includes a set of firm and industry characteristics that might affect a firm's future innovation output (e.g., Aghion et al. 2005; Lerner, Sorensen, and Strömberg 2011). In particular, we control for firm size, age, asset tangibility, capital expenditures, R&D expenditures, profitability, leverage, equity, and (the square of) product market competition. Further, we also control for a set of bank and bank-firm characteristics that could influence firms' innovation output. We control for the length of the firm-bank relationship (Herrera and Minetti 2007), the geographic diversification of the banks (Deng, Mao, and Xia 2021), the number of lending relationships that a firm maintains to proxy for bilateral versus multilateral financing (Bhattacharya and Ritter 1983; Bhattacharya and Chiesa 1995), bank concentration (Saidi and Streitz

respectively.[20] The error term is represented by $\epsilon_{f,b,s,t}$ and is clustered by firm. The coefficient estimate of interest in this regression model is β, which captures the average effect of bank specialization on firms' innovation output. If Hypothesis 1 holds, we expect the coefficient estimate of β to be positive and statistically significant.

The results of estimating this equation are presented in Table 3. Across the three columns, the outcome variable is a binary variable equal to one if a firm developed a product innovation, process innovation, or world-first innovation. As explained earlier, product innovations refer to new or significantly improved goods or services, while process innovations refer to new or significantly improved methods of production or logistics. A world-first innovation is defined as an innovation that has never been introduced anywhere else in the world.

The coefficient estimates of *Bank specialization* in Table 3 are statistically insignificant in all columns, with p-values between 0.4 and 0.9, which is far from the conventional significance levels. This suggests that, inconsistent with Hypothesis 1, bank specialization does not have a positive effect on firms' innovation output, on average.

As explained earlier, this could be due to the fact that the positive effect of bank specialization on firms' innovation output is mitigated by banks' concern about asset overhang. Therefore, we turn to Hypothesis 2 and investigate how bank specialization affects firms' innovation output depending on the asset overhang of the sector in which a firm operates. To this end, we extend the previous equation by adding an interaction term between the sectoral specialization of a firm's lender and the asset overhang of the sector in which the firm operates. Formally, we estimate the following model:

$$\begin{aligned} y_{f,b,s,t} =& \beta \textit{Bank specialization}_{b,s,t-1} + \delta(\textit{Bank specialization}_{b,s,t-1} \times \textit{Asset overhang}_{s,t-1}) \\ &+ \gamma C_{f,b,s,t-1} + \lambda_{s,t} + \lambda_{l,t} + \epsilon_{f,b,s,t} \end{aligned} \tag{3}$$

where $\textit{Asset overhang}_{s,t-1}$ corresponds to capital intensity of sector s in year $t-1$ (see Section 3.2). Asset overhang measures are standardized (meaning that each measure has a mean

2021; Aghion et al. 2005), and the market share of a bank in a specific sector (Giannetti and Saidi 2019). Note that while banks' sectoral specialization measures the importance of a sector for a bank, banks' market share measures the importance of a bank for a sector. Table O5 in the Online Appendix shows that the correlation between these two variables is relatively modest ($\rho = -0.11$). Variable definitions are provided in Table A1.

[20] Sector-by-time fixed effects control for sector-specific time-varying unobserved heterogeneity, such as differences in financing or patenting behavior across sectors. The locality-by-time fixed effects control for region-specific time-varying unobserved heterogeneity, such as local economic policies and business cycles.

equal to zero and a standard deviation equal to one), with values below zero corresponding to low asset overhang sectors and values above zero corresponding to high asset overhang sectors. The coefficient of interest in this regression model is δ, which captures how the effect of bank specialization on firms' innovation output varies depending on the asset overhang of the sector in which a firm operates. If Hypothesis 2 holds, we expect the coefficient estimate of δ to be negative and statistically significant.

The results are presented in Table 4. In columns (1) and (3), we find a significantly negative coefficient estimate for the interaction term between *Bank specialization* and *Asset overhang*. Thus, our coefficient estimates indicate that the effect of bank specialization on firms' innovation output is positive in sectors with low asset overhang, and negative in sectors with high asset overhang, which is consistent with Hypothesis 2. These effects are economically significant. The coefficient estimates in columns (1) and (3) indicate that, in sectors with low (high) asset overhang, a one standard deviation increase in lenders' sectoral specialization increases (decreases) the probability of introducing product innovations and world-first innovations by 10% and 35%, respectively, compared to the sample average. The coefficient estimate in column (2) is statistically insignificant, which is not unexpected, as process innovations generally have smaller spillover effects compared to product innovations (e.g., Aghion et al. 2022).

In sum, we uncover a novel pattern that has not been predicted or documented by previous papers; bank specialization has a positive (negative) effect on the innovation output of firms operating in sectors with low (high) asset overhang. Our results thus indicate that bank specialization, a defining feature of banks' business models, acts as an important channel through which the banking sector could enhance or distort corporate innovation and economic growth.

4.2 External Validity: Evidence from the U.S.

We complement the analyses with insights from the U.S. by combining syndicated loan data with patent data. Using those data and the regression models specified in Equations (2) and (3), we study the effect of lenders' sectoral specialization on firms' patent output, and how this effect depends on the asset overhang of the sector in which a firm operates. We make

two small modifications to our estimation model. First, since patent count and citations are count-based measures, we employ a fixed effects Poisson model rather than OLS. Research has shown that the latter can yield biased estimates in linear regression models that apply a logarithmic transformation to count data, whereas the former provides consistent and reasonably efficient estimates under more general conditions (see Cohn, Liu, and Wardlaw 2022; Wooldridge 1999).[21] Second, in addition to the set of controls used in our baseline regressions, we also control for firms' growth opportunities (proxied by Tobin's Q) and access to public debt financing (proxied by a dummy variable equal to one if a firm has a public debt rating and zero otherwise, as in Atanassov 2016). Unlike the small (private) firms in our Belgian data sample, firms borrowing in the U.S. syndicated loan market may have access to alternative financing options. If these financing alternatives are correlated with firms' innovation activities, not controlling for these factors may bias our coefficient estimates.

The results are presented in Table 5. Columns (1) and (4) indicate that, on average, bank specialization does not have a significant impact on firms' innovation output. However, consistent with our baseline findings, we find that this effect depends on the underlying asset overhang. As discussed in Section 3.2, we measure asset overhang in our U.S. analysis using two approaches: asset redeployability and product market rivalry. The specific measure used in each regression is indicated at the bottom of the table. Consistent with our earlier findings, columns (2)–(3) and (5)–(6) of Table 5 show a significantly negative coefficient for the interaction term between bank specialization and asset overhang. This suggests that in sectors characterized by low (high) asset overhang, lenders' sectoral specialization has a positive (negative) effect on both the quantity and quality of firms' patent output. In terms of economic magnitude, the coefficient estimates in columns (2) and (5) imply that, in sectors with low (high) asset overhang, a one standard deviation increase in bank specialization is associated with a 12% increase (decrease) in the number of patent citations. Consistent with a bank lending mechanism, Table A2 in the Appendix further shows that these results are more pronounced for bank-dependent firms (defined as firms that lack a long-term credit

[21] As shown in Wooldridge (1999), the fixed effects Poisson estimator is fully robust to any kind of variance-mean relationship, meaning that there is no need to "correct" for overdispersion when using fixed effects Poisson models, one simply needs to compute robust standard errors. In contrast, the fixed effects Negative Binomial estimator is very fragile to violation of a set of assumptions that are very strong (also see Cohn, Liu, and Wardlaw 2022; Guimaraes 2008).

rating, as in Chava and Purnanandam 2011; Kashyap, Lamont, and Stein 1994).

Overall, our results obtained from the U.S. syndicated loan data combined with patent data are in line with our baseline results using the Belgian sample. This confirms the robustness of our finding that lenders' sectoral specialization can enhance or impede innovation depending on the underlying asset overhang, and highlights that this finding holds for different types of firms and across different geographies. Leveraging the U.S. dataset thus lends credibility to the external validity of our findings.

4.3 Exploring the Mechanisms: Financial Contracting

Our analysis so far shows that bank specialization has heterogeneous effects on corporate innovation and that these heterogeneous effects stem from differences in asset overhang across sectors. However, a question that remains to be answered is the channel through which these heterogeneous effects arise. To address this question, we draw on prior literature and focus on the main channel through which banks can affect firms' investments, namely financing conditions.

We start with the CIS survey, which contains a question on firms' access to external financing (available for two of the survey waves in our sample). Specifically, firms are asked whether the lack of access to external financing constitutes a significant obstacle to their innovation activities. Using this self-reported information, we use a linear probability model to examine the likelihood that a firm responds affirmatively to this question, depending on the specialization of its bank and the asset overhang of the sector it operates in. The results are presented in Table 6. Consistent with a bank lending mechanism, the significantly positive interaction term in column (2) implies that firms borrowing from specialized banks and operating in sectors with low (high) asset overhang are around 10 percentage points less (more) likely to report external financing issues as a significant barrier to their innovation activities.

Then, to further dig into this channel, we leverage the richness of the Belgian credit register and U.S. syndicated loan data. In particular, we extend the approach of Blickle, Parlatore, and Saunders (2024) to analyze how bank specialization affects firms' loan conditions, and whether this effect depends on the innovativeness and asset overhang of the sector in which a

firm operates. To implement this approach, we transform both the Belgian credit register and U.S. syndicated loan data to the bank-firm-year level and estimate the following OLS regression:

$$\begin{aligned} y_{f,s,b,t} = & \beta_1 Bank\ specialization_{b,s,t-1} + \\ & \beta_2 (Bank\ specialization_{b,s,t-1} \times Innovative_{s,t-1}) + \\ & \beta_3 (Bank\ specialization_{b,s,t-1} \times High\ asset\ overhang_{s,t-1}) + \\ & \beta_4 (Bank\ specialization_{b,s,t-1} \times Innovative_{s,t-1} \times High\ asset\ overhang_{s,t-1}) + \\ & \delta C_{f,b,s,t-1} + \lambda_{b,t} + \lambda_{f,t} + \epsilon_{f,b,s,t} \end{aligned} \tag{4}$$

where the outcome variable $y_{f,s,b,t}$ corresponds to the loan conditions offered on loans by bank b to firm f operating in sector s at time t. $Bank\ specialization_{b,s,t-1}$ corresponds to our measure of bank specialization as defined in Section 3.1. $Innovative_{s,t-1}$ is a dummy variable equal to one for innovative sectors and zero otherwise, which ensures that we focus on how banks' lending policies affect firms' innovation activities. Innovative sectors are defined as sectors with above-average product or process innovations (in Belgium) or above-average patents (in the U.S.) in year $t-1$ (similar to Chava et al. 2013). $High\ asset\ overhang_{s,t-1}$ is a dummy variable equal to one if sector s is characterized by high asset overhang in year $t-1$, and zero otherwise. A sector with high asset overhang is defined based on the top terciles of each of our measures of asset overhang as defined in Section 3.2. $C_{f,s,t-1}$ corresponds to the vector of control variables used in our main analysis. In the analysis based on Belgian credit register data, we include bank-by-time and firm-by-time fixed effects, denoted by $\lambda_{b,t}$ and $\lambda_{f,t}$, respectively. The former accounts for bank-specific time-varying unobserved heterogeneity, such as differences in aggregate credit supply or regulatory requirements, while the latter controls for firm-specific time-varying unobserved heterogeneity, such as differences in credit demand. In the U.S. syndicated loan analysis, the data structure does not permit the inclusion of firm-by-time fixed effects; instead, we use sector-by-time and firm fixed effects in those regressions. The error term, $\epsilon_{f,b,s,t}$, is double-clustered at the bank and sector level. The coefficient of interest is β_4, which captures the potential differences in borrowing terms offered by more (versus less) specialized banks to innovative (versus non-innovative) sectors with high (versus low) asset overhang.

Tables 7 and 8 report the results based on the Belgian credit register and U.S. syndicated

loan data, respectively.[22] At the bottom of each table, we report the measure of asset overhang as well as the fixed effects used in the corresponding regressions. For brevity, we primarily focus our discussion on the results from the Belgian credit register data, as the results from the U.S. syndicated loan data lead to very similar conclusions.

First, we study the loan rates. If banks are aware of the potential negative spillovers of technology-induced shocks, we would expect them to charge higher loan rates to compensate for that risk. The results from testing this conjecture are presented in column (1) of Table 7. Note that, as the Belgian credit register does not contain detailed data on loan rates, we proxy firms' cost of debt as total interest expenses divided by total financial debt (derived from firms' financial statements). The coefficient estimates in column (1) indicate that specialized banks charge a 6 percentage points higher loan rate to firms in innovative sectors with high asset overhang. The results reported in Table 8 based on the U.S. syndicated loan data are similar.[23] Together, these findings are consistent with our hypothesis that specialized banks are aware of the potential negative spillovers of technology-induced shocks and require compensation to take on this risk.

Second, we study collateral requirements. If banks anticipate negative spillovers from technology-induced shocks, they may require higher collateral from firms in innovative sectors with high asset overhang to mitigate potential losses. The results in column (2) of Table 7 support this conjecture. Specifically, the coefficient estimates in this column imply that a one standard deviation increase in bank specialization raises the likelihood of loan collateralization by 6 percentage points for firms in innovative sectors with high asset overhang.

Due to limited data on collateral in LPC DealScan, we focus on loan covenants instead of collateral in the U.S. syndicated loan sample. If banks internalize the potential impact of technology-induced shocks, they can impose restrictive covenants to limit firms' financial and operational flexibility, which is essential for long-term high-risk innovation projects (Chava and Roberts 2008; Nini, Smith, and Sufi 2009).[24] Consistent with this conjecture, column (4)

[22]The results in Tables 7 and 8 contain the full set of interaction terms outlined in Equation (4). Tables O8 and O9 in the Online Appendix report the baseline effect of bank specialization, without any of the interaction terms. The results of the baseline effect estimates are consistent with those reported by Blickle, Parlatore, and Saunders (2024) and Giometti, Güler, and Pietrosanti (2022) for the U.S., and De Jonghe, Mulier, and Samarin (2025) for Belgium.

[23]In these regressions, we measure loan rates as the all-in-drawn spread (AISD), as is common in the literature.

[24]Covenant violations shift control rights to lenders, enabling them to recall or renegotiate loans, impose penalties, and influence borrowers' financial and investment decisions by forcing asset divestitures or a shift toward lower-risk, short-term projects. Hence, covenants significantly impact firms' financial strategies (Chava and Roberts 2008; Nini, Smith, and Sufi 2009;

of Table 8 for example, implies that a one standard deviation increase in bank specialization is associated with a 10% increase in covenant strictness for firms in innovative sectors with high asset overhang.

Third, we analyze debt maturity, based on the premise that short loan maturities create liquidity or refinancing risk.[25] Since firms' propensity to innovate depends on their ability to finance ongoing R&D expenditures and secure future borrowing to cover potential adjustment costs, refinancing risk can hinder innovation (Aghion et al. 2010; Hall and Lerner 2010). The estimates in column (3) of Table 7 indicate that specialized banks are significantly less likely to grant long-term loans to firms in innovative sectors with a high asset overhang. This finding is consistent across both the Belgian and U.S. data samples and supports the notion that specialized banks impose restrictive loan conditions on firms in innovative sectors with high asset overhang, thereby limiting their propensity to innovate.

Fourth, column (4) of Table 7 reports results with loan amounts as the outcome variable. Consistent with previous papers, we find that bank specialization is associated with larger loan amounts, but we do not find evidence that this differs for firms operating in innovative sectors with high asset overhang. The results are similar in the U.S. sample (as shown in the last two columns of Table 8).

An additional feature of the Belgian credit register, unavailable in the U.S. syndicated loan data, is that it contains the proprietary credit ratings assigned by banks to their borrowers. These credit ratings represent banks' estimated probability of default (PD) for each borrower, ranging from 0 to 1, and enable us to directly test whether specialized banks perceive firms in innovative sectors with high asset overhang as riskier. The results are presented in Table 9. Column (1) shows that specialized banks assign significantly lower PDs to borrowers within their sector of specialization, potentially reflecting superior screening and monitoring capabilities, as suggested by Blickle et al. (2020) and Blickle et al. (2025). However, consistent with our hypothesis, the triple interaction term in column (2) demonstrates that specialized

Roberts and Sufi 2009). For example, Nini, Smith, and Sufi (2009) find that 32% of loan contracts explicitly restrict capital expenditures, limiting investment. Although covenants rarely directly restrict innovation, they can do so indirectly, as most are tied to firms' net worth or debt-to-EBITDA ratios (Chava and Roberts 2008). Because innovation inputs like R&D are expensed immediately, they lower EBITDA and net worth, potentially forcing firms to scale back innovation to comply with covenant thresholds (Deng, Mao, and Xia 2021).

[25] Refinancing risk arises when firms face less favorable conditions upon refinancing due to changes in market conditions or capital market imperfections (Froot, Scharfstein, and Stein 1993). Furthermore, lenders may underestimate the firm's continuation value at the time of refinancing, potentially preventing refinancing altogether (Diamond 1991, 1993).

banks assign higher PDs to firms operating in innovative sectors with high asset overhang. The coefficient estimate implies that one standard deviation increase in bank specialization is associated with a 20% increase compared to the average PD, which means that the effect is economically significant. This finding further supports the notion that banks are aware of the potential negative spillovers of technology-induced shocks on their legacy loan portfolios.

Taken together, our results indicate that the heterogeneous effects of bank specialization on corporate innovation are attributable to banks' traditional role as financiers of firms' investments (as in Amore, Schneider, and Žaldokas 2013; Deng, Mao, and Xia 2021; Granja and Moreira 2023; Herrera and Minetti 2007). In sectors with low asset overhang, innovative firms obtain better loan conditions from specialized banks, which allows them to invest more in long-term, risky projects, leading to an improvement in innovation output. In contrast, in sectors with high asset overhang, innovative firms obtain worse loan conditions from specialized banks, which curtails their investments in long-term, risky projects, leading to a reduction in innovation output. These findings hold both using Belgian credit register data and U.S. syndicated loan data, again illustrating the robustness and generalizability of our conclusions across distinct institutional settings.

5. Robustness

In this section, we conduct a series of additional tests to assess the robustness of our findings. Since the data required for several of these analyses are available only for the U.S., and certain tests are designed to address concerns specific to the U.S. setting, we restrict these robustness checks to the U.S. sample. In doing so, we restrict the robustness tests to the findings from columns (2)–(3) and (5)–(6) of Table 5.

5.1 Endogeneity

A central empirical challenge in assessing the effect of bank specialization on firm innovation is the potential for endogeneity. A first concern is reverse causality in that banks choose to specialize in sectors that already exhibit high innovation. A second concern is endogenous matching between banks and firms. For example, innovative firms may seek out specialized lenders. Finally, omitted variables—such as sector-specific shocks or firm-level innovation

capacity—could simultaneously influence both bank behavior and firm outcomes. To mitigate these concerns and strengthen causal inference, our baseline models control for a broad range of firm and bank characteristics as well as fixed effects, reducing the possibility of omitted variable bias. To address the endogeneity of bank specialization, we use mergers between U.S. banks as plausibly exogenous shocks to bank specialization, allowing us to isolate the effect of specialization changes unrelated to firm characteristics. Second, to address endogenous matching, we examine whether innovative firms systematically match with specialized banks at the onset of their lending relationship.

First, following prior research, we exploit mergers between U.S. banks active in the syndicated loan market as a source of exogenous variation in banks' sectoral specialization (e.g., Giannetti and Saidi 2019; Iyer et al. 2022).[26] Specifically, we compare how the innovation output of borrowers from target banks changes after the target banks' sectoral specialization alters due to the acquisition by acquirer banks. Mimicking an event study design, we analyze innovation output during the six years surrounding bank mergers. This approach ensures that changes in bank specialization are due to mergers and accounts for the fact that it may take a few years for the impact to be fully measurable. We then compute a variable $\Delta Bank\ specialization_{b,s}^{merger}$ which is equal to $Bank\ specialization_{acquirer,s,t,t+3} - Bank\ specialization_{target,s,t-3,t}$. In essence, this variable captures the merger-induced change in bank specialization for borrowers of the target banks (De Jonghe, Mulier, and Samarin 2025), which we use to run the following regression model:

$$\begin{aligned}\Delta y_{f,b,s} =& \beta \Delta Bank\ specialization_{b,s}^{merger} + \delta(\Delta Bank\ specialization_{b,s}^{merger} \times Asset\ overhang_s) \\ &+ \gamma C_{f,b,s} + \lambda_s + \lambda_l + \epsilon_{f,b,s}\end{aligned} \tag{5}$$

where $\Delta y_{f,b,s}$ is the change in (the natural logarithm of) the average patent quantity or quality of firm f three years before versus three years after the year in which its lender was acquired in a merger. We include the vector of control variables used in our baseline model, as well as sector and state fixed effects. Note that we estimate Equation (5) using OLS as

[26] We follow previous papers and restrict our focus to U.S. bank mergers between two BHCs that each have at least $1 billion in assets preceding the merger. We are unable to conduct the bank merger analysis using the Belgian sample, as only one merger occurred during our sample period. De Jonghe, Mulier, and Samarin (2025) analyze this merger case, in which Landbouwkrediet (translation: Agricultural Credit) acquired Centea Bank in 2013 and subsequently rebranded as Crelan Bank. This merger involved two relatively small banks and affected only a limited number of firms in our Belgian data sample. Consequently, we rely on the U.S. sample to exploit multiple merger deals rather than focusing on a single case.

Poisson models cannot be used for outcome variables with negative values.

The results reported in Table A3 in the Appendix show that merger-induced changes in bank specialization have a positive (negative) effect on firms' innovation output in sectors with low (high) asset overhang (the coefficient estimate in column (2) has a p-value of 0.17). The economic magnitudes of these estimates are comparable to those of our baseline estimates. For instance, column (3) of Table A3 indicates that a one standard deviation increase in bank specialization leads to a 6% increase (decrease) in patent citations in sectors with low (high) asset overhang. Taken together, these results support that our baseline estimates are reliable in terms of identification and inference.

Second, to further address endogeneity concerns, we test for endogenous matching between banks and firms. For example, in sectors with high (low) asset overhang, less (more) innovative firms might be systematically more likely to borrow from more (less) specialized banks. While this seems unlikely, we adopt an approach similar to Foà et al. (2019) to examine the relationship between a firm's innovation output and a bank's specialization at the time of their initial lending relationship, and how this relationship varies with sector-level asset overhang. We aggregate the syndicated loan data at the firm-bank-year level and estimate the following model:

$$\begin{aligned} y_{f,b,s,t} =& \beta Bank\ specialization_{b,s,t-1} + \delta(Bank\ specialization_{b,s,t-1} \times Asset\ overhang_{s,t-1}) \\ &+ \delta C_{f,b,s,t-1} + \lambda_{s,t} + \lambda_{l,t} + \epsilon_{f,b,s,t} \end{aligned} \tag{6}$$

where f, s, b, and t denote firm, sector, bank, and year, respectively. The outcome variable is the number of patents or citations by firm f in the three years prior to its first loan with bank b. Control variables are consistent with our baseline model, with additional bank-level controls to account for other potential drivers of firm-bank matching. Note that this analysis is conducted at the firm-bank-year level using only observations from the first time that a firm and a bank engaged in a lending relationship (that is, the first time that a firm and a bank "matched").

Results presented in Table A4 in the Appendix reveal no evidence of endogenous matching; the coefficient on δ is statistically insignificant across all specifications. This suggests our results are not driven by systematic matching of more (less) innovative firms with more (less)

specialized banks in sectors with low (high) asset overhang.

5.2 Alternative Channels

We examine several alternative channels that could explain our results. First, we consider zombie lending (i.e., bank lending to non-viable firms that would otherwise exit). De Jonghe, Mulier, and Samarin (2025) show that bank specialization reduces zombie lending, while Schmidt et al. (2023) find that zombie lending impedes innovation. This suggests that bank specialization could reduce zombie lending and, in turn, increase innovation. To test this alternative explanation, we re-estimate our baseline while controlling for banks' sectoral zombie lending. We follow Banerjee and Hofmann (2022) in defining zombie firms as those with an interest coverage ratio[27] below one and a Tobin's Q below the sector median for two consecutive years. A firm exits zombie status only after both conditions are violated for two consecutive years. Using this definition, we construct a bank-level measure of zombie lending as the share of credit to zombie firms within a sector-year relative to the bank's total lending in that sector-year:[28]

Panel A of Table A5 in the Appendix presents the results. Consistent with Schmidt et al. (2023), zombie lending has a significantly negative effect on patent count, though we find no effect on citations.[29] Crucially, controlling for sectoral zombie lending does not alter our main result, as the interaction between bank specialization and asset overhang remains qualitatively and quantitatively unchanged.[30]

Second, we examine whether our results could be explained by banks' technological conservatism—a mechanism proposed by Minetti (2011) in the context of relationship lending. Minetti (2011) argues that information gathered by banks during lending relationships is often tied to mature technologies and may not be easily transferable to new technologies.

[27] The interest coverage ratio is earnings before interest and taxes divided by interest payments.

[28] Specifically, banks' sectoral zombie lending is measured as:

$$Bank\ zombie\ lending_{b,s,t} = \frac{\sum_{f=1}^{F^s} Credit_{b,f,s,t} \times Zombie_{f,t}}{\sum_{s=1}^{S}\sum_{f=1}^{F^s} Credit_{b,f,s,t}} \tag{7}$$

where $Credit_{b,f,s,t}$ is bank b's credit to firm f in sector s at time t, and $Zombie_{f,t}$ equals one if firm f is a zombie. F^s and S denote the number of firms in sector s and total sectors, respectively.

[29] Schmidt et al. (2023) examine patent count but not citations. One possible explanation for our findings is that zombie lending may cause firms to abandon less promising projects and focus on core innovations, reducing the number of patents but not their average citation count (Lerner, Sorensen, and Strömberg 2011).

[30] One concern could be that our asset overhang measures are correlated with the share of zombie firms. In unreported tests, we find our baseline results hold when splitting the sample by the proportion of zombie firms across sectors.

Anticipating this loss of informational value, banks may resist financing technological change to preserve the relevance of their proprietary information. To test this, we re-estimate our baseline model including an interaction between bank specialization and a dummy for firms operating in informationally complex sectors, where conservatism is more likely to be relevant. Following Rauch (1999), we classify sectors by product type; those with goods traded on organized exchanges, reference-priced goods, and goods with neither. As in prior work (e.g., Cao et al. 2023; Iyer et al. 2022), we define "complex" sectors as those with products not traded on exchanges or reference-priced, and "simple" sectors as the rest.[31] We re-estimate Equation (3) including the interaction between bank specialization and the informational complexity dummy. Panel B of Table A5 shows that the interaction between bank specialization and asset overhang remains similar to our baseline results, while the interaction with informational complexity is insignificant. In short, informational complexity does not appear to drive our results.

In addition to ruling out the two channels above, we test whether other interaction terms between asset overhang and observable bank characteristics, such as market share or competition, might generate effects similar to the interaction between asset overhang and bank specialization. As shown in Table O10 in the Online Appendix, the interaction between asset overhang and bank specialization remains consistently negative and statistically significant, while no such pattern emerges for the other interactions. This confirms the relevance of the mechanism we identify.

Finally, one may worry that bank specialization is correlated with unobserved firm- or bank-specific characteristics. To address this, we show that our results hold when saturating the model with stricter fixed effects. Panel A of Table O11 in the Online Appendix shows that including firm fixed effects, which account for unobserved, time-invariant firm heterogeneity, does not affect our findings.[32] Panel B shows that our results are also robust to including bank-by-time fixed effects, which control for time-varying bank-specific factors potentially influencing both specialization and firm innovation.[33]

[31] In our sample, about 30% of firms are classified as having heterogeneous products, consistent with Campello and Gao (2017) and Cao et al. (2023).

[32] These regressions involve fewer observations since firm fixed effects in Poisson models limit the sample to firms that patent at least once during the sample period.

[33] These regressions are based on firms with one bank (a single lead arranger) to avoid duplicate innovation observations. Unreported analyses confirm similar results when using the full sample and weighting observations by each bank's share of firm

5.3 Intensive versus Extensive Margin

Our baseline results show that bank specialization does not influence firm-level innovation overall but has a negative (positive) effect in sectors with high (low) asset overhang. We next examine whether this result is driven by the extensive or intensive margin of firms' innovation activities.

First, we assess the extensive margin by analyzing patent entry and exit. Patent entry is defined as a binary variable equal to one if a firm files at least one patent in year t but none in $t-1$; exit equals one if the firm filed at least one patent in $t-1$ but not in t. We estimate linear probability models to test whether the effect of bank specialization on these outcomes depends on sector level asset overhang. Panels A and B of Table A6 in the Appendix show the results for entry and exit, respectively. To ensure valid identification, Panel A is restricted to firm-year observations where firms did not patent in $t-1$, while Panel B includes only firms that patented in $t-1$. This ensures, for example, that, for patent entry, we compare the likelihood that two otherwise similar non-patenting firms in $t-1$—one borrowing from a specialized bank and one from a non-specialized bank—start patenting in t. Across all specifications, we find insignificant estimates for both the baseline effect of bank specialization and its interaction with asset overhang. This suggests that bank specialization does not affect the extensive margin of firms' innovation, regardless of asset overhang.

Second, to examine the intensive margin, we analyze the effect of bank specialization on patents and citations for firms that filed at least one patent during the sample period. Conceptually, this is similar to using firm fixed effects, though the latter also controls for time-invariant firm-specific heterogeneity. Results are presented in Table A7 in the Appendix. Consistent with our main findings, the baseline effect of bank specialization on patent quantity and quality is insignificant. However, when accounting for sectoral asset overhang, we find that bank specialization has a significantly positive (negative) effect on innovation in sectors with low (high) asset overhang. These results confirm that bank specialization influences innovation through the intensive rather than the extensive margin. This aligns with our findings from Section 4.3, where we show that specialized lenders offer worse (better) loan

credit.

terms to firms in innovative (non-innovative) sectors with high (low) asset overhang.

5.4 Patent Novelty

In our U.S. analysis, the outcome variables are the number of patents and patent citations. While citations reflect a patent's scientific and economic impact, they do not clearly distinguish between incremental and radical (breakthrough) innovations. This distinction matters because radical innovations are typically riskier, more influential, and more important for long-term economic growth (Acemoglu 2008; Caggese 2019). To differentiate between incremental and radical innovation, we follow the literature and use patent generality and originality as measures of novelty (Trajtenberg, Henderson, and Jaffe 1997).[34] Patent generality captures the breadth of technological fields that build on a patent, while originality reflects the diversity of prior knowledge a patent recombines.

Panel A of Table O12 in the Online Appendix reports results from re-estimating Equation (3) using patent generality and originality as outcomes. Since both are continuous variables ranging from 0 to 1, we estimate these regressions using OLS. The results show that bank specialization increases patent novelty in sectors with low asset overhang and reduces it in sectors with high asset overhang, consistent with earlier findings. These effects are economically meaningful. For example, Column (1) indicates that in low (high) overhang sectors, a one standard deviation increase in bank specialization is associated with a 5% increase (decrease) in patent originality.

Panel B shows that among innovating firms, these effects are driven by the intensive margin, as in our main results. Overall, these findings suggest that bank specialization influences not only the quantity and quality of innovation, but also its radicalness—an important result, given the role of radical innovation in driving long-term growth (Acemoglu 2008).

5.5 Additional Robustness Checks

We provide a series of additional robustness checks, detailed in the Online Appendix, confirming that our results remain robust to alternative measures of bank specialization, variations

[34] Generality is calculated as $1 - \sum_{j=1}^{N_j} f_{ij}^2$, where f_{ij} is the share of citations to patent i from technology class j, and N_j is the number of distinct International Patent Classification (IPC) classes. A high generality score means a patent is cited across many fields, indicating broad impact. Originality is similarly calculated as $1 - \sum_{j=1}^{N_j} b_{ij}^2$, where b_{ij} is the share of cited patents from class j. A high originality score means the patent draws from diverse prior technologies.

in data samples and measurement choices, as well as alternative estimation methods and model specifications.

6. Conclusion

In this paper, we study how lenders' sectoral specialization affects firms' innovation activities. Theoretically, this effect is ambiguous. On the one hand, bank specialization improves banks' screening and monitoring capabilities (Blickle, Parlatore, and Saunders 2024; Blickle et al. 2025). Given that innovation requires investments in opaque, risky assets (Rajan and Zingales 2001), specialized banks may be more inclined to support firms' innovation activities. On the other hand, the innovation activities of one firm can adversely affect other firms, for instance through business stealing (Aghion and Howitt 1992; Bloom, Schankerman, and Van Reenen 2013). Since bank specialization increases banks' exposure to the potential spillovers of such technology-induced shocks, specialized banks may be more inclined to impede the development of new technologies.

We examine this research question in two complementary institutional environments. Our first dataset combines micro-level innovation survey data with credit register data from a representative European country (Belgium). Our second dataset combines U.S. syndicated loan data with patent data. Based on both datasets, we show that the effect of bank specialization on corporate innovation depends on the underlying asset overhang, which is the risk that a new technology adversely affects the value of a bank's legacy loan portfolio (Degryse, Roukny, and Tielens 2024). Using three distinct measures of asset overhang, we find that bank specialization enhances (impedes) firms' innovation output in sectors with low (high) asset overhang. The economic mechanism underlying these results runs through banks' role in financing firms' investments, as specialized banks tend to offer more (less) favorable loan conditions to firms operating in innovative sectors with low (high) asset overhang. This implies that banks internalize the potential risk of technology-driven negative spillovers on their legacy loan portfolios, which in turn influences firms' financing conditions and propensity to undertake innovative projects.

Overall, our study documents a novel channel through which the banking sector affects

corporate innovation. Our findings imply that product market characteristics—such as capital intensity, asset redeployability, and product market rivalry—impact banks' incentives to finance innovation, thereby contributing to our understanding on how financial and product markets interact.

Supplementary Material

Supplementary material is available at Review of Finance online.

Data Availability

The data underlying this article are either derived from a source in the public domain, provided under license by a third party, or confidential due to its restricted regulatory use.

Confidential data include the National Bank of Belgium's restricted access data from the corporate credit register, the firms' annual accounts and income statements, and banks' balance sheets. Information on these data sources can be found at https://www.nbb.be/en/activities/central-credit-registers/corporate-credit-register-ccr, https://www.nbb.be/en/central-balance-sheet-office, and https://www.nbb.be/doc/cp/fr/ki/circ/pdf/book1_20-05-2014.pdf (in French). The datasets themselves are confidential and cannot be disclosed. (On-site) Access to the confidential data used for this project may be obtained with Data Use Agreements with the National Bank of Belgium. Researchers interested in access to the data may contact Olivier De Jonghe (olivier.dejonghe@nbb.be).

Other confidential data include the Belgian Community Innovation Survey data managed by the Belgian Science Policy Office. Information on these data sources can be found at https://meri.belspo.be/site/innovation_en.stm. The datasets themselves are confidential and cannot be disclosed. Access to the confidential data used for this project may be obtained with Data Use Agreements with the Belgian Science Policy Office.

Public domain data used in this article are asset redeployability data from Kim and Kung (2017) (available from https://www.dropbox.com/scl/fi/rxpges91vpgijcx47jq04/redeployability_data_RFS_2024v.zip?rlkey=qkp3sd3j5ujguutxkd0t170n3&e=1&dl=0); product market rivalry data from Bloom, Schankerman, and Van Reenen (2013) (available from https://www.dropbox.

com/scl/fi/dfqseu94ok0j8u5d01q58/bsv_replication.zip?rlkey=jul9ao6u1a7opwuj45tg0vjyu&e=1&dl=0); loan covenant strictness data from Demerjian and Owens (2016) (available from https://peterdemerjian.weebly.com/managerialability.html); DealScan-BHC linking table from Chakraborty, Goldstein, and MacKinlay (2018) (available from https://sites.google.com/site/acmackinlay/data); BHC merger data from the Federal Reserve Bank of Chicago (available from https://www.chicagofed.org/banking/financial-institution-reports/merger-data).

Data owned by third-party vendors used in this article include DealScan syndicated loan data and Chava and Roberts (2008)'s DealScan-Compustat linking table obtained from WRDS; firm financial statement data obtained from Compustat; patent data obtained from PATSTAT.

The code used to convert the raw data into the final dataset used in the analysis, programs used to generate the final published output from the final dataset, detailed instructions for use as well as log-files to demonstrate that the code runs have been shared with the Review of Finance.

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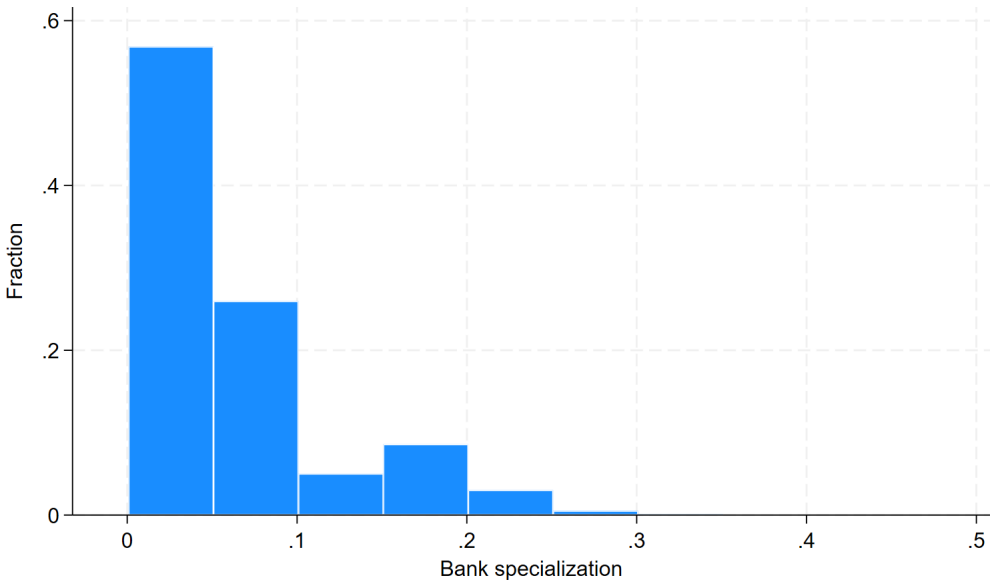
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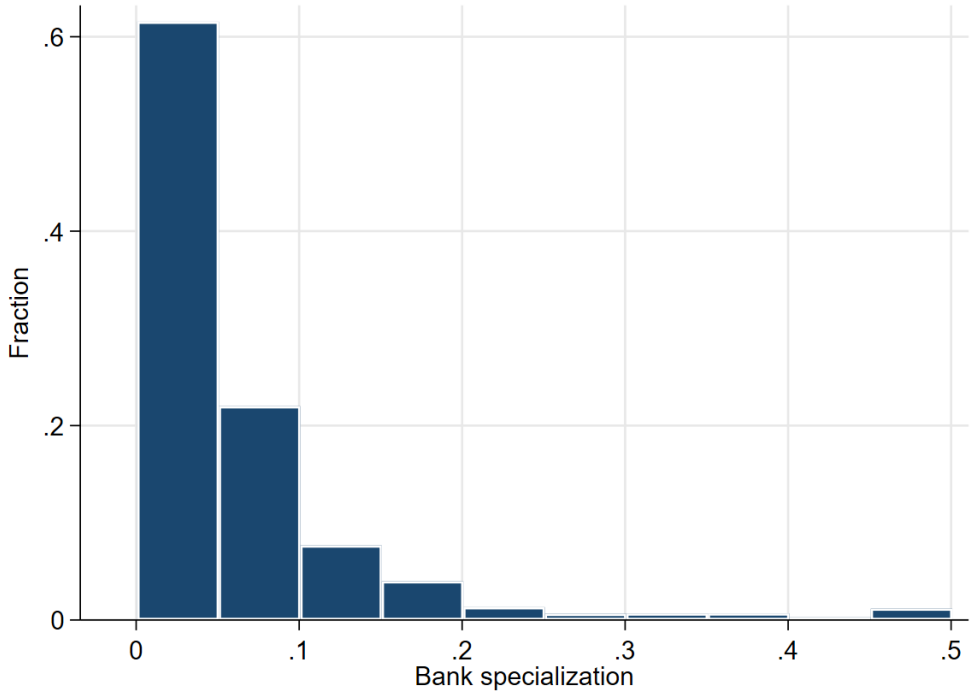
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Figures

Figure 1. The distribution of banks' sectoral specialization



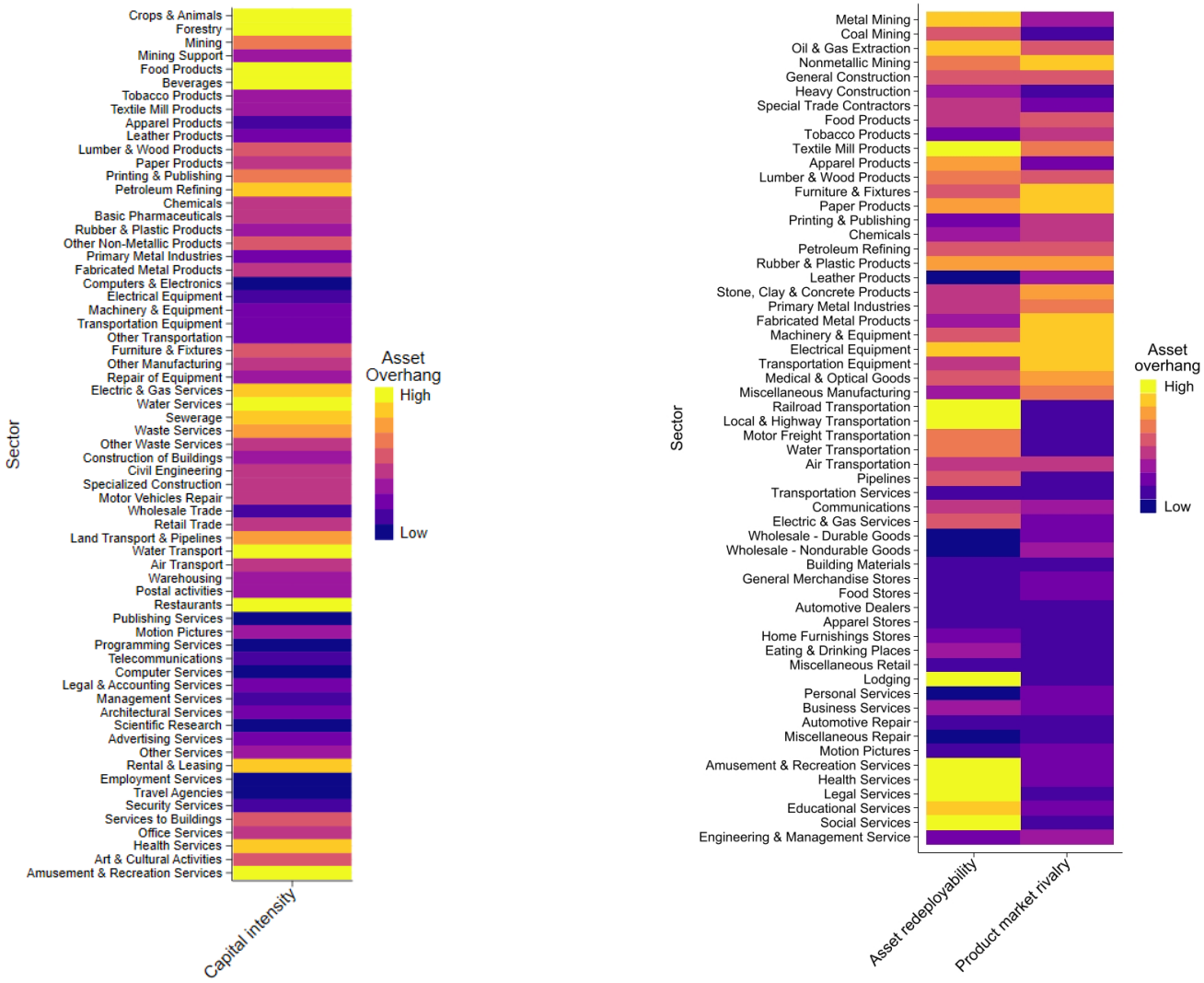
(a) Belgian credit register data



(b) U.S. syndicated loan data

Note: This histogram presents the distribution of bank specialization based on the Belgian credit register in Panel (a) and the U.S. syndicated loan data in Panel (b). In both panels, the histogram shows on the X-axis bins of bank specialization values and on the Y-axis the fraction of bank-sector-year combinations in that specific bin. Both panels show that, while the loans to a particular sector usually represent less than 5% of a bank's loan portfolio, there are instances in which a particular sector represents more than 30% of a bank's loan portfolio. Thus, banks seem to specialize by concentrating their lending disproportionately in a few sectors.

Figure 2. Heat map of the degree of asset overhang across sectors



(a) Belgian sample (b) U.S. sample

Note: This figure presents a heat map of the degree of asset overhang across sectors based on the Belgian sample in Panel (a) and based on the U.S. sample in Panel (b). For each sector, we compute the average of the standardized value of asset overhang, using each of our three measures of asset overhang described in Section 3.2. The heat map then assigns a color to each value, with brighter (yellow) colors corresponding to a higher degree of asset overhang, and darker (purple) colors to a lower degree of asset overhang.

Tables

Table 1. Summary statistics: Belgian data sample

	N	Mean	Median	SD	P5	P95
Product innovation	15,158	0.39	0.00	0.49	0.00	1.00
Process innovation	15,158	0.60	1.00	0.49	0.00	1.00
New-to-world innovation	12,002	0.07	0.00	0.25	0.00	1.00
Size	15,158	15.59	15.46	1.68	13.01	18.92
Age	15,158	27.98	25.00	17.20	6.00	60.00
Leverage/TA	15,158	0.63	0.64	0.26	0.20	0.97
Equity/TA	15,158	0.36	0.34	0.26	0.04	0.78
Cash/TA	15,158	0.13	0.08	0.15	0.00	0.46
EBIT/TA	15,158	0.07	0.06	0.12	–0.08	0.27
Fixed assets/TA	15,158	0.24	0.19	0.21	0.01	0.67
CAPEX/TA	15,158	–0.00	–0.00	0.07	–0.08	0.10
R&D expenses/TA	15,158	0.03	0.00	0.24	0.00	0.14
HHI	15,158	0.05	0.02	0.07	0.01	0.18
Bank specialization	15,158	0.05	0.02	0.06	0.00	0.18
Bank market share	15,158	0.22	0.24	0.08	0.06	0.32
Bank geographic diversification	15,158	0.01	0.00	0.01	0.00	0.04
Bank concentration	15,158	0.23	0.23	0.04	0.19	0.29
Lending relationship length	15,158	11.46	12.00	5.42	2.00	20.00
Number of lending relationships	15,158	1.87	2.00	0.91	1.00	4.00
Capital intensity	15,158	0.00	–0.22	1.00	–1.22	2.03

Note: This table presents summary statistics of the variables used in our main empirical analysis. Variable definitions are provided in Table A1 in Appendix. Our sample comprises yearly firm level data from Belgian firms covered in the Community Innovation Survey waves between 2008 and 2020 and that borrow from at least one bank active in the Belgian loan market.

Table 2. Summary statistics: Belgian data sample:
Innovating versus non-innovating firms

	Innovating firms		Non-innovating firms		
	Mean	SD	Mean	SD	Difference
Product innovation	0.49	0.50	0.00	0.00	0.49***
Process innovation	0.75	0.43	0.00	0.00	0.75***
New-to-world innovation	0.09	0.28	0.00	0.00	0.09***
log(Total assets)	15.76	1.67	14.92	1.52	0.83***
Age	28.33	17.43	26.58	16.17	1.75***
Debt/TA	0.62	0.25	0.65	0.29	–0.02***
Cash/TA	0.13	0.15	0.14	0.16	–0.01**
EBIT/TA	0.08	0.12	0.06	0.13	0.01***
Fixed assets/TA	0.24	0.21	0.27	0.23	–0.03***
CAPEX/TA	–0.00	0.07	–0.00	0.08	0.00
R&D expenses/TA	0.04	0.26	0.00	0.07	0.04***
Equity/TA	0.36	0.25	0.34	0.28	0.02***
HHI	0.05	0.07	0.04	0.06	0.00
Bank specialization	0.05	0.06	0.06	0.07	–0.01***
Bank market share	0.23	0.07	0.22	0.08	0.00**
Bank concentration	0.23	0.04	0.23	0.03	0.01***
Bank geographic diversification	0.01	0.01	0.01	0.02	0.00*
Number of lending relationships	1.90	0.92	1.73	0.86	0.17***
Lending relationship length	11.65	5.42	10.72	5.37	0.93***
Capital intensity	–0.05	0.99	0.18	1.00	0.22***
Observations	12,126		3,032		15,158

Note: This table presents summary statistics of the variables used in our main empirical analysis. We distinguish between innovating firms (i.e., firms with at least one product or process innovations over the sample period) and non-patenting firms (i.e., firms with zero product or process innovations over the sample period). For each group, we report the mean and standard deviation of the main variables. We also report the difference in means, and whether this difference is significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively. Variable definitions are provided in Table A1 in Appendix. Our sample comprises yearly firm level data from Belgian firms covered in the Community Innovation Survey waves between 2008 and 2020 and that borrow from at least one bank active in the Belgian loan market.

Table 3. Bank specialization and corporate innovation: Belgian innovation survey data

	(1) Product innovation	(2) Process innovation	(3) World-first innovation
Bank specialization$_{t-1}$	–0.13	0.17	0.08
	(0.42)	(0.42)	(0.19)
Observations	15,157	15,157	12,001
Adjusted R-squared	0.14	0.11	0.06
Controls	Yes	Yes	Yes
Sector × Time FE	Yes	Yes	Yes
Region × Time FE	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on Belgian firms' innovation output, using self-reported information on firms' innovation activities from the Community Innovation Survey. Across the different columns, the outcome variable corresponds to a dummy variable that is equal to one if a firm introduced a product innovation, process innovation, or world-first innovation. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 4. Bank specialization, asset overhang, and corporate innovation: Belgian innovation survey data

	(1) Product innovation	(2) Process innovation	(3) World-first innovation
Bank specialization$_{t-1}$	–0.43	0.20	–0.12
	(0.46)	(0.44)	(0.18)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.78*	0.07	–0.47**
	(0.45)	(0.43)	(0.22)
Observations	15,157	15,157	12,001
Adjusted R-squared	0.14	0.11	0.06
Asset overhang measure	Capital intensity	Capital intensity	Capital intensity
Controls	Yes	Yes	Yes
Sector × Time FE	Yes	Yes	Yes
Region × Time FE	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on Belgian firms' innovation output, depending on the asset overhang of the sector in which a firm operates, using self-reported information on firms' innovation activities from the Community Innovation Survey. Across the different columns, the outcome variable corresponds to a dummy variable that is equal to one if a firm introduced a product innovation, process innovation, or world-first innovation. Across the different columns, the measure of asset overhang is sector-year level capital intensity as indicated at the bottom of the table. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 5. Bank specialization and corporate innovation: U.S. data sample

	Patents			Citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank specialization$_{t-1}$	–0.03	0.38	0.88	0.29	0.42	0.65
	(0.57)	(0.56)	(0.64)	(0.38)	(0.38)	(0.45)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$		–1.51**	–1.38**		–1.53***	–0.81**
		(0.70)	(0.54)		(0.48)	(0.38)
Observations	24,209	24,209	24,209	24,035	24,035	24,035
Pseudo R-squared	0.71	0.71	0.71	0.36	0.36	0.36
Asset overhang measure		Asset redeployability	Product market rivalry		Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output, depending on the asset overhang of the sector in which a firm operates. In the first three columns, the outcome variable is the number of patents filed by a firm in a given year. In the last three columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 6. Bank specialization, asset overhang, and external financing: Belgian innovation survey data

	(1) Innovation obstructed due to external financing problems	(2) Innovation obstructed due to external financing problems
Bank specialization$_{t-1}$	0.30	1.23
	(0.56)	(0.89)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$		2.09*
		(1.21)
Observations	3,753	3,753
Adjusted R-squared	0.04	0.04
Asset overhang measure		Capital intensity
Controls	Yes	Yes
Sector × Time FE	Yes	Yes
Region × Time FE	Yes	Yes

Note: This table shows the effect of bank specialization on Belgian firms' access to external financing, depending on the asset overhang of the sector in which a firm operates. The outcome variable corresponds to a dummy variable that is equal to one if a firm reported a lack of access to external financing as a significant obstacle to its innovation activities. The measure of asset overhang is sector-year level capital intensity as indicated at the bottom of the table. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 7. Bank specialization, asset overhang, and loan conditions: Belgian credit register data

	(1) Cost of debt	(2) Pr(Loan collateralized)	(3) Pr(New long-term debt)	(4) ln(Loan amount)
Bank specialization$_{t-1}$	0.38	0.14	–0.06	3.79
	(0.26)	(0.24)	(0.15)	(4.60)
... × Innovative$_{t-1}$	–0.58**	–0.09	0.10	–0.29
	(0.28)	(0.12)	(0.15)	(5.08)
... × High asset overhang$_{t-1}$	–0.83**	–0.72	0.24	5.74
	(0.39)	(0.44)	(0.18)	(5.72)
... × Innovative$_{t-1}$ × High asset overhang$_{t-1}$	1.04**	1.25***	–0.41**	4.47
	(0.52)	(0.45)	(0.16)	(4.88)
Observations	142,037	168,587	168,587	168,587
Adjusted R-squared	0.45	0.18	0.03	0.21
Asset overhang measure	Capital intensity	Capital intensity	Capital intensity	Capital intensity
Controls	Yes	Yes	Yes	Yes
Firm×Year FE	No	Yes	Yes	Yes
Bank×Year FE	No	Yes	Yes	Yes
Sector×Year FE	Yes	No	No	No
Firm FE	Yes	No	No	No

Note: This table shows the effect of bank specialization on borrowers' loan conditions, depending on the innovativeness and the asset overhang of the sector in which a firm operates. Across the different columns, the outcome variable is the ratio of interest expenses over total financial debt, a dummy variable equal to one for collateralized loans, a dummy variable equal to one for new long-term loan originations, and the natural logarithm of the total loan amount. The innovative sector dummy variable is equal to one for sectors with above-average product and process innovations. The high asset overhang dummy variable is equal to one if the corresponding measure of asset overhang is in the top tercile. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2, and variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are double clustered at the bank and sector level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 8. Bank specialization, asset overhang, and loan conditions: U.S. syndicated loan data

	ln(AISD)		Pr(Loan covenant violation)		ln(Loan maturity)		ln(Loan amount)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank specialization$_{t-1}$	–0.03	0.01	–0.44**	–0.17	0.27*	0.25	1.57***	1.52***
	(0.18)	(0.15)	(0.17)	(0.16)	(0.15)	(0.16)	(0.27)	(0.28)
... × Innovative$_{t-1}$	0.20	–0.30	0.44**	0.10	–0.27	0.44	–0.10	0.32
	(0.22)	(0.23)	(0.21)	(0.25)	(0.26)	(0.32)	(0.54)	(1.00)
... × High asset overhang$_{t-1}$	–0.11	–0.29	–0.39	–1.02***	0.19	0.15	–0.42	–0.10
	(0.24)	(0.35)	(0.39)	(0.18)	(0.19)	(0.14)	(0.32)	(0.30)
... × Innovative$_{t-1}$ × High asset overhang$_{t-1}$	0.67**	0.99**	1.04*	1.16***	0.31	–1.02**	0.45	–0.41
	(0.34)	(0.45)	(0.61)	(0.42)	(0.32)	(0.42)	(0.85)	(1.35)
Observations	13,969	13,969	5,046	5,046	15,421	15,421	15,452	15,452
Adjusted R-squared	0.72	0.72	0.46	0.46	0.41	0.41	0.78	0.78
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on borrowers' loan conditions, depending on the innovativeness and the asset overhang of the sector in which a firm operates. Across the different columns, the outcome variable is the natural logarithm of the all-in-drawn-spread, loan covenant strictness, the natural logarithm of loan maturity, and the natural logarithm of the total loan amount. The innovative sector dummy variable is equal to one for sectors with above-average product and process innovations. The high asset overhang dummy variable is equal to one if the corresponding measure of asset overhang is in the top tercile. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2, and variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are double clustered at the bank and sector level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table 9. Bank specialization, asset overhang, and loan conditions: Belgian credit register data: Banks' proprietary credit risk assessment

	(1) Probability of default	(2) Probability of default
Bank specialization$_{t-1}$	–0.08***	–0.05
	(0.02)	(0.06)
... × Innovative$_{t-1}$		–0.02
		(0.06)
... × High asset overhang$_{t-1}$		–0.09
		(0.07)
... × Innovative$_{t-1}$ × High asset overhang$_{t-1}$		0.14***
		(0.04)
Observations	168,587	168,587
Adjusted R-squared	0.30	0.30
Asset overhang measure		Capital intensity
Controls	Yes	Yes
Bank×Year FE	Yes	Yes
Firm×Year FE	Yes	Yes

Note: This table shows the effect of bank specialization on borrowers' estimated probability of default, depending on the innovativeness and the asset overhang of the sector in which a firm operates. The outcome variable is the estimated probability of default assigned by the bank to the borrower. The innovative sector dummy variable is equal to one for sectors with above-average product and process innovations. The high asset overhang dummy variable is equal to one if the corresponding measure of asset overhang is in the top tercile. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2, and variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are double clustered at the bank and sector level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Appendix

Table A1. Variable definitions

Variable	Description
Product innovation	Binary variable equal to one if a firm reports having introduced new or significantly improved goods or services.
Process innovation	Binary variable equal to one if a firm reports having introduced new or significantly improved methods of production or logistics, among others
World-first innovation	Binary variable equal to one if a firm reports having introduced an innovation that has never been introduced anywhere else in the world.
Patents	Total number of patents filed (and eventually granted) by a firm.
Patent citations	Average number of five-year ahead forward-citations per patent filed (and eventually granted) by a firm.
Patent originality	Average breadth of the (IPC) technological fields that a firm's patents rely on (i.e., knowledge diversity behind a firm's patent).
Patent generality	Average breadth of (IPC) technological fields of later generations of inventions that benefit from a firm's patents.
Size	The natural logarithm of a firm's total assets.
Age	The number of years since Initial Public Offering (IPO) for firms in the U.S. data sample, and the number of years since foundation for firms in the Belgian data sample.
Debt/TA	The ratio of debt to total assets.
Equity/TA	The ratio of equity to total assets.
Cash/TA	The ratio of cash to total assets.
Fixed assets/TA	The ratio of fixed assets to total assets.
CAPEX/TA	The ratio of capital expenditures to total assets.
R&D expenses/TA	The ratio of R&D expenses to total assets.
ROA	The ratio of net income to total assets.
HHI	The Herfindahl–Hirschman index of the annual sales from firms within a (3-digit SIC) sector.
Tobin's Q	The market-to-book ratio.
Public debt rating	A dummy variable equal to one if a firm has a public debt rating and zero otherwise.
Bank specialization	The fraction of credit granted by a bank to a given sector relative to the total credit granted by that bank.
Bank market share	The fraction of credit granted by a bank to a given sector relative to the total bank credit in that sector.
Bank concentration	The Herfindahl–Hirschman index of credit granted by banks within a given year and (3-digit SIC) sector.
Bank geographic diversification	The Herfindahl-Hirschman index of credit granted by a bank to borrowers in a given year and state.
Number of lending relationships	The total number of banks with which a firm maintains a lending relationship.
Lending relationship length	The average number of years during which a firm and a bank have maintained a lending relationship.
Asset redeployability	The sector-year level average of category level asset redeployability scores computed by Kim and Kung (2017).
Product market rivalry	The sector-year level average of firms' product market rivalry scores computed by Bloom, Schankerman, and Van Reenen (2013).
Capital intensity	The sector-year level average of firms' fixed assets to total assets.

Table A2. Robustness: U.S. data sample: Heterogeneity in bank dependence

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Bank-dependent borrowers				
Bank specialization$_{t-1}$	–0.16	–0.19	0.35	0.53
	(0.58)	(0.67)	(0.40)	(0.50)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.95*	–0.42	–1.90***	–0.83*
	(0.55)	(0.38)	(0.60)	(0.43)
Observations	12,283	12,283	12,128	12,128
Pseudo R-squared	0.65	0.65	0.34	0.34
Panel B: Non-bank-dependent borrowers				
Bank specialization$_{t-1}$	1.04	1.68	0.84	1.14
	(0.84)	(1.18)	(0.78)	(0.93)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–2.40*	–1.91	–0.78	–0.91
	(1.27)	(1.41)	(1.19)	(1.04)
Observations	8,934	8,934	8,916	8,916
Pseudo R-squared	0.69	0.69	0.42	0.42
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of sector in which a firm operates, for more versus less bank-dependent firms. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Panel A reports results for more bank-dependent firms (identified as those without long-term credit rating, as in Chava and Purnanandam 2011). Panel B reports results for less bank-dependent firms. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A3. Robustness: U.S. data sample: Bank mergers as a source of exogenous variation in bank specialization

	Δln(1+patents)		Δln(1+citations)	
	(1)	(2)	(3)	(4)
ΔBank specialization$^{\text{Merger implied}}$	–0.19	–0.20	–0.15	–0.18
	(0.25)	(0.29)	(0.37)	(0.39)
ΔBank specialization$^{\text{Merger implied}}$ × Asset overhang	–0.56*	–0.59	–0.71*	–0.81*
	(0.34)	(0.38)	(0.39)	(0.46)
Observations	1,813	1,813	1,813	1,813
Adjusted R-squared	0.18	0.18	0.18	0.18
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of sector in which a firm operates, using bank mergers as a source of exogenous variation in bank specialization. In the first two columns, the outcome variable is the change in the average number patents filed from borrowers of target banks three years before versus three years after the target bank was involved in a bank merger. In the last two columns, the outcome variable is the change in the average number patent citations of patents from borrowers of target banks three years before versus three years after the target bank was involved in a bank merger. $\Delta Bank\ specialization^{merger\ implied}$ is computed as the average sectoral specialization of the acquirer bank in the three years after the merger minus the average sectoral specialization of the target bank in the three years before the merger. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A4. Robustness: U.S. data sample: Sorting

	$\text{Patents}_{[t-3,t-1]}$		$\text{Citations}_{[t-3,t-1]}$	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	–0.88	–1.13	–0.73	–1.05
	(0.70)	(0.85)	(0.52)	(0.64)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.36	0.12	–0.33	0.25
	(0.63)	(0.62)	(0.53)	(0.51)
Bank size$_{t-1}$	0.20**	0.20**	0.03	0.03
	(0.10)	(0.10)	(0.07)	(0.07)
Bank deposits/TA$_{t-1}$	0.24	0.23	0.28	0.27
	(0.33)	(0.33)	(0.29)	(0.29)
Bank equity/TA$_{t-1}$	1.72	1.76	0.15	0.25
	(3.41)	(3.45)	(2.81)	(2.83)
Bank LLP/TA$_{t-1}$	9.52	9.98	0.23	0.17
	(15.16)	(15.12)	(12.33)	(12.35)
Bank ROA$_{t-1}$	-12.78	-12.05	–6.52	–5.88
	(10.38)	(10.27)	(8.29)	(8.21)
Bank market share$_{t-1}$	–0.04	–0.03	–0.30	–0.29
	(0.31)	(0.31)	(0.28)	(0.28)
Bank geographic diversification$_{t-1}$	–0.28	–0.28	–0.20	–0.20
	(0.24)	(0.24)	(0.19)	(0.19)
Bank concentration$_{t-1}$	–0.48	–0.50	0.26	0.25
	(0.33)	(0.33)	(0.27)	(0.27)
Observations	3,401	3,401	3,401	3,401
Adjusted R-squared	0.72	0.72	0.35	0.35
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates, while controlling for potential alternative channels. In the first two columns, the outcome variable is the average number of patents filed by a firm in the three years before the firm started borrowing from bank b for the first time. In the last two columns, the outcome variable is the average number of forward-citations by the patents filed by a firm in the three years before the firm started borrowing from bank b for the first time. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A5. Robustness: U.S. data sample: Alternative channels

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Controlling for banks' sectoral zombie lending				
Bank specialization$_{t-1}$	0.39	0.93	0.42	0.65
	(0.56)	(0.63)	(0.38)	(0.45)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.51**	–1.43***	–1.53***	–0.81**
	(0.69)	(0.54)	(0.48)	(0.39)
Bank zombie lending$_{t-1}$	–5.01**	–5.30***	0.36	0.23
	(1.97)	(1.97)	(1.63)	(1.64)
Observations	24,209	24,209	24,035	24,035
Pseudo R-squared	0.71	0.71	0.36	0.36
Panel B: Controlling for sectoral complexity				
Bank specialization$_{t-1}$	0.82	0.96	0.15	0.21
	(0.95)	(0.95)	(0.65)	(0.64)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.49**	–1.32**	–1.51***	–0.81**
	(0.69)	(0.53)	(0.48)	(0.38)
Bank specialization$_{t-1}$ × Complex$_{t-1}$	–0.70	–0.12	0.45	0.75
	(1.12)	(1.12)	(0.79)	(0.80)
Observations	24,209	24,209	24,035	24,035
Pseudo R-squared	0.72	0.72	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates, while controlling for potential alternative channels. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Panel A includes a control for banks' (sectoral) zombie lending, as defined in Section 5.2. Panel B includes a control for the interaction between bank specialization and the informational complexity of a sector, as defined in Section 5.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A6. Robustness: U.S. data sample: Extensive margin

Panel A: Patent entry	(1)	(2)	(3)
Bank specialization$_{t-1}$	–0.00	–0.00	–0.00
	(0.02)	(0.02)	(0.03)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$		–0.00	–0.01
		(0.02)	(0.03)
Observations	20,275	20,275	20,275
Adjusted R-squared	0.06	0.06	0.06
Panel B: Patent exit	**(1)**	**(2)**	**(3)**
Bank specialization$_{t-1}$	–0.12	–0.12	–0.14
	(0.12)	(0.13)	(0.15)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$		–0.04	0.03
		(0.13)	(0.12)
Observations	5,513	5,513	5,513
Adjusted R-squared	0.17	0.17	0.17
Asset overhang measure		Asset redeployability	Product market rivalry
Sector×Year FE	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output, depending on the asset overhang of the sector in which a firm operates. In Panel A, the outcome variable is a binary variable that captures patent entry. In Panel B, the outcome variable is a binary variable that captures patent exit. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table A7. Robustness: U.S. data sample: Intensive margin

	Patents			Citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank specialization$_{t-1}$	0.00	0.11	0.01	0.25	0.13	0.10
	(0.43)	(0.42)	(0.42)	(0.28)	(0.29)	(0.29)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$		–0.73*	–0.45		–0.80***	–0.40*
		(0.38)	(0.34)		(0.25)	(0.21)
Observations	9,923	9,923	9,923	9,916	9,916	9,916
Pseudo R-squared	0.71	0.71	0.71	0.36	0.36	0.36
Asset overhang measure		Asset redeployability	Product market rivalry		Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output, depending on the asset overhang of the sector in which a firm operates. The sample is restricted to firms that filed at least one patent over the sample period. In Panel A, the outcome variable is the number of patents filed by a firm in a given year. In Panel B, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. In the even (odd) columns, we do (not) include firm fixed effects. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

ONLINE APPENDIX

Bank Specialization and Corporate Innovation

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O.1. Additional Information on U.S. Data Sample Construction

The data sources used to construct the U.S. data sample are merged as follows. First, we merge the firm financial statement data from Compustat with the syndicated loan data from LPC DealScan using the Compustat-DealScan link provided by Chava and Roberts (2008). This results in a firm-bank-year level dataset which, for each firm-bank pair in a given year, records the firm's financial variables and the sectoral specialization of the bank with which the firm has an active lending relationship. Following prior literature, firms and banks are considered to have an active lending relationship from the moment a loan is originated until the moment the loan matures, including the years when no new loan is originated (Chakraborty, Goldstein, and MacKinlay 2018). We then aggregate this data to a firm-year level dataset. Specifically, for firms that borrow from more than one bank, we use the weighted bank specialization of the banks from which the firm borrows (weighted by the share of each bank's loan exposure in the firm's entire loan exposure). Since 70% of the firms in our sample borrow from only one (lead arranger) bank, this aggregation affects only a limited set of firms.[a] Second, we match this data with the innovation measures computed from PATSTAT using the linking table from Arora, Belenzon, and Sheer (2021). In doing so, we follow the innovation literature and set patent outcomes equal to zero for firm-year observations that are not matched to the patent database. Finally, we match this data with our two measures of asset overhang (based on 2-digit SIC codes). Ultimately, this yields a firm-year level dataset with information on firms' innovation output, firms' financial statements and asset overhang, and the sectoral specialization of firms' lenders.

O.2. Additional Robustness Checks

O.2.1 Alternative Measures of Bank Specialization

We re-estimate our baseline results using alternative measures of bank specialization. First, in Panel A of Table O13 in the Online Appendix, we compute bank specialization as the fraction of the number of borrowers that a bank has in a given sector relative to the total number of borrowers that a bank has in its entire loan portfolio in a given year. Compared

[a] To mitigate potential concerns related to this aggregation, robustness tests discussed in the paper show that our results hold using the sample of firms with only one (lead arranger) bank relationship.

to our baseline measure of bank specialization, this alternative measure accounts for the fact that specialization in a certain sector could be driven by one or a few large borrowers, which would limit the scope of learning through repeated lending and the scope of negative spillovers on other firms in a bank's legacy loan portfolio. Second, in Panel B of Table O13 in the Online Appendix, we compute bank specialization based on 3-digit instead of 2-digit SIC codes. To be consistent, the measures of asset overhang and the sector-by-time fixed effects in these regressions are also based on 3-digit instead of 2-digit SIC codes. Despite these technical differences, we find in line with our baseline results that in sectors with low (high) asset overhang, bank specialization positively (negatively) affects firms' innovation output.

O.2.2 Data Sample and Measurement

We conduct various robustness checks related to the composition of our data sample and measurement choices. First, Panel A of Table O14 in the Online Appendix shows that our results hold using the lead arranger definition of Ivashina (2009) instead of the lead arranger definition of Chakraborty, Goldstein, and MacKinlay (2018). Second, Panel B of Table O14 in the Online Appendix shows that our results hold if we use lead arranger's exact loan share instead of attributing the entire loan amount to the lead arranger in order to compute bank specialization, which addresses potential concerns about measurement error.

Third, while the Belgian credit register data covers all corporate loans, syndicated loans are only a fraction of lenders' entire loan portfolio. This could raise concerns that, for some bank-sector-time bins, our measure of bank specialization based on syndicated loan data is computed from a small number of loans, which could lead to measurement error. To mitigate this concern, Panel A of Table O15 in the Online Appendix shows that our results hold if we drop bank-sector-time bins for which we have less than ten distinct loans to compute a lender's sectoral specialization. Fourth, unlike the Belgian credit register, the syndicated loan data only capture loan originations and do not provide information on outstanding loan amounts. To mitigate potential concerns that any of our U.S. findings could be biased due to the assumption that loans remain "active" for their full maturity, Panel B of Table O15 shows that our results hold if we compute bank specialization based solely on the loan

volumes granted by bank b to firms operating in sector s during year t.

Fifth, for firms borrowing from multiple (lead arranger) banks, our baseline regressions are estimated using the weighted average of the sectoral specialization of those firms' lenders. Although more than 70% of the observations correspond to firms with a single lender, one could be concerned that using a weighted measure of bank specialization generates noise in our estimates. To resolve any remaining concerns, Panel A of Table O16 in the Online Appendix shows that our results are robust to restricting our data sample to firms that borrow from a single (lead arranger) bank, for which we do not have to use a weighted average of bank specialization. Finally, our baseline regressions are estimated using data from 1996 until 2013, which covers two crisis periods. This could raise concerns that our results might be influenced by the (direct) effects of crises on corporate innovation (e.g., Babina, Bernstein, and Mezzanotti 2023; Nanda and Nicholas 2014) or the (indirect) effects of crises on specialized banks' lending policies, which could, in turn, influence firms' investments (e.g., De Jonghe et al. 2020). To verify that this is not the case, Panel B of Table O16 in the Online Appendix shows that our results hold if we exclude recession periods (as defined by the NBER Business Cycle Dating Committee).

O.2.3 Empirical Model

Our results are robust to alternative estimation methods and specifications. Panels A and B of Table O17 in the Online Appendix respectively show that our results hold if we cluster standard errors at the sector or bank level instead of the firm level, and Table O18 in the Online Appendix shows that our results hold if we estimate our baseline regression using OLS instead of a Poisson model. Further, a potential limitation of our baseline regression model is that it assumes the estimated effect to have the same economic magnitude in sectors with low and high asset overhang. To relax this assumption, we estimate the following equation:

$$\begin{aligned} y_{f,b,s,t} =& \delta_1 Bank\ specialization_{b,s,t-1}^{Low\ asset\ overhang} + \delta_2 Bank\ specialization_{b,s,t-1}^{High\ asset\ overhang} \\ &+ \gamma C_{f,b,s,t-1} + \lambda_{s,t} + \lambda_{l,t} + \epsilon_{f,b,s,t} \end{aligned} \tag{8}$$

where δ_1 and δ_2 capture the effect of bank specialization on corporate innovation in sectors with a normalized asset overhang value below and above zero, respectively. The results of

estimating Equation (8) are presented in Table O19 in the Online Appendix. This table shows that the positive coefficient estimates of δ_1 are slightly larger than the negative coefficient estimates of δ_2, implying that not only the sign but also the magnitude of the effect depends on the asset overhang of the sector in which a firm operates.

Tables

Table O1. Main characteristics of the Belgian and U.S. datasets

	Belgian sample	U.S. sample
Data source	Belgian input to the European Community Innovation Survey + firm financial statement data + Belgian credit register data	Patent data + firm financial statement data + U.S. syndicated loan data
Period	2008–2020	1996–2013
Asset overhang measure	Capital intensity	Asset redeployability & Product market rivalry
Strengths	1. Captures all types of innovation 2. Mitigates patent-secrecy trade-offs 3. Covers small firms heavily reliant on bank financing	1. Allows to construct more granular measures of asset overhang 2. Enables to use bank mergers as exogenous variation in bank specialization 3. Enables robustness tests unavailable in the Belgian setting

Note: This table presents the key characteristics and comparative advantages of each of the two datasets used in our analyses.

Table O2. Summary statistics: U.S. data sample

	N	Mean	Median	SD	P5	P95
Patents	32,041	5.12	0.00	17.23	0.00	39.00
Patent citations	32,041	2.00	0.00	5.82	0.00	11.63
Patent originality	32,041	0.10	0.00	0.22	0.00	0.67
Patent generality	32,041	0.17	0.00	0.34	0.00	0.94
Size	32,041	6.51	6.49	1.87	3.45	9.81
Age	32,041	3.51	0.00	5.43	0.00	15.00
Debt/TA	32,041	0.32	0.28	0.25	0.00	0.76
Equity/TA	32,041	0.39	0.39	0.23	0.00	0.78
Cash/TA	32,041	0.07	0.03	0.10	0.00	0.28
ROA	32,041	–0.00	0.03	0.20	–0.25	0.14
Fixed assets/TA	32,041	0.57	0.51	0.39	0.06	1.30
CAPEX/TA	32,041	0.06	0.04	0.06	0.01	0.20
R&D expenses/TA	32,041	0.02	0.00	0.06	0.00	0.12
Tobin's Q	32,041	0.78	0.46	1.20	0.00	2.72
Public debt rating	32,041	0.72	1.00	0.45	0.00	1.00
HHI	32,041	0.19	0.15	0.14	0.04	0.50
Bank specialization	32,041	0.06	0.03	0.08	0.00	0.21
Bank market share	32,041	0.15	0.10	0.15	0.00	0.44
Bank concentration	32,041	0.29	0.26	0.14	0.14	0.57
Bank geographic diversification	32,041	0.86	0.94	0.19	0.47	0.99
Number of lending relationships	32,041	1.39	1.00	0.73	1.00	3.00
Lending relationship length	32,041	4.13	3.00	2.99	1.00	10.00
Asset irredeployability	32,041	–0.00	–0.12	1.00	–1.76	1.69
Product market rivalry	32,041	0.00	–0.33	1.00	–1.13	1.61

Note: This table presents summary statistics for the loan outcomes used in the analyses in Section 4.3. Panel A contains summary statistics for the loan outcomes from the Belgian credit register data. Panel B contains summary statistics for the loan outcomes from the U.S. syndicated loan data. All variables are measured at the bank-firm level, except for the cost of debt in Panel A; Due to a lack of interest rate data in the Belgian credit register, cost of debt is calculated as a firm's total interest expenses over total financial debt. Variable definitions are provided in Table A1 in Appendix.

Table O3. Summary statistics: U.S. data sample:
Patenting versus non-patenting firms

	Patenting firms		Non-patenting firms		
	Mean	SD	Mean	SD	Difference
Patents	17.42	28.22	0.00	0.00	–17.42***
Patent citations	6.81	9.09	0.00	0.00	–6.81***
Patent originality	0.35	0.28	0.00	0.00	–0.35***
Patent generality	0.58	0.41	0.00	0.00	–0.58***
Size	6.81	1.90	6.38	1.84	–0.42***
Age	3.88	5.97	3.36	5.18	–0.52***
Debt/TA	0.25	0.20	0.34	0.27	0.09***
Equity/TA	0.44	0.22	0.37	0.23	–0.07***
Cash/TA	0.10	0.11	0.06	0.10	–0.03***
ROA	0.01	0.20	–0.00	0.20	–0.01***
Fixed assets/TA	0.50	0.32	0.60	0.41	0.10***
CAPEX/TA	0.05	0.04	0.07	0.06	0.02***
R&D expenses/TA	0.05	0.08	0.01	0.05	–0.04***
Tobin's Q	1.18	1.54	0.62	0.97	–0.56***
Public debt rating	0.93	0.26	0.64	0.48	–0.29***
HHI	0.21	0.15	0.18	0.14	–0.03***
Bank specialization	0.05	0.07	0.06	0.09	0.01***
Bank market share	0.16	0.16	0.14	0.14	–0.02***
Bank concentration	0.32	0.15	0.28	0.14	–0.03***
Bank geographic diversification	0.87	0.18	0.86	0.20	–0.02***
Number of lending relationships	1.39	0.74	1.38	0.73	–0.01
Lending relationship length	4.39	3.06	4.03	2.96	–0.36***
Observations	9414		22627		32041

Note: This table presents summary statistics of the main variables used in our empirical analysis. We distinguish between patenting firms (i.e., firms with at least one patent over the sample period) and non-patenting firms (i.e., firms with zero patents over the sample period). For each group, we report the mean and standard deviation of the main variables. We also report the difference in means, and whether this difference is significant at the 10%, 5%, and 1% levels using *, **, and ***, respectively. Variable definitions are provided in Table A1 in Appendix. Our sample comprises yearly firm level data from U.S. firms borrowing in the syndicated loan market between 1996 and 2013.

Table O4. Summary statistics: Patents and patent citations

	Median	75%	85%	90%	95%	99%	Max	Mean	SD	Observations
Panel A: Patents	0	0	3	10	39	89	89	5.1	17.2	32,041
Panel B: Citations	0	0	5	7.5	11.6	25.7	82.9	2.0	5.8	32,041

Note: This table presents summary statistics of the main patent outcomes used in our empirical analysis. Panel A is based on the number of patents filed by firms in a given year. Panel B is based on the average number of forward-citations received by the patents filed by firm in a given year. Our sample comprises yearly firm level data from U.S. firms borrowing in the syndicated loan market between 1996 and 2013.

Table O5. Correlation table: Belgian data sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Size	1.000															
(2) Age	0.282	1.000														
(3) Debt/TA	–0.101	–0.213	1.000													
(4) Equity/TA	0.191	0.205	–0.963	1.000												
(5) Cash/TA	–0.091	–0.046	–0.286	0.291	1.000											
(6) ROA	–0.002	–0.010	–0.277	0.296	0.222	1.000										
(7) Fixed assets/TA	–0.043	–0.044	0.136	–0.115	–0.220	–0.105	1.000									
(8) CAPEX/TA	0.006	0.010	–0.002	0.002	–0.047	–0.072	0.165	1.000								
(9) R&D expenses/TA	–0.011	–0.039	0.012	–0.014	0.051	–0.024	–0.072	0.011	1.000							
(10) HHI	0.075	0.047	–0.039	0.034	–0.019	–0.057	0.038	0.006	0.070	1.000						
(11) Bank specialization	0.078	0.093	–0.021	0.029	–0.069	0.020	–0.111	0.000	–0.060	–0.298	1.000					
(12) Bank market share	0.052	0.080	–0.037	0.038	0.001	0.009	–0.033	0.002	0.001	0.026	–0.107	1.000				
(13) Bank concentration	0.072	0.037	–0.045	0.040	–0.022	–0.024	–0.013	–0.001	–0.006	0.202	–0.308	0.138	1.000			
(14) Bank geographic diversification	0.062	0.014	0.036	–0.037	0.006	0.007	–0.083	–0.019	0.034	–0.009	0.028	–0.115	–0.038	1.000		
(15) Number of lending relationships	0.113	0.121	0.062	–0.065	–0.151	–0.052	0.076	0.001	–0.031	0.010	0.046	–0.096	–0.019	–0.058	1.000	
(16) Lending relationship length	0.082	0.332	–0.098	0.102	–0.054	0.032	0.077	–0.014	–0.073	–0.007	0.074	0.133	0.015	–0.090	0.307	1.000

Note: This table presents the correlations between the main variables used in our empirical analysis using Belgian data. Variable definitions are provided in Table A1 in Appendix. Our sample comprises yearly firm level data from Belgian firms covered in the Community Innovation Survey waves between 2008 and 2020 and that borrow from at least one bank active in the Belgian loan market.

Table O6. Correlation table: U.S. data sample

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Size	1.000																	
(2) Age	–0.027	1.000																
(3) Debt/TA	0.072	–0.049	1.000															
(4) Equity/TA	–0.203	0.117	–0.691	1.000														
(5) Cash/TA	–0.208	0.064	–0.278	0.298	1.000													
(6) ROA	0.222	0.000	–0.165	0.180	–0.148	1.000												
(7) Fixed assets/TA	0.153	–0.040	0.157	–0.092	–0.232	0.031	1.000											
(8) CAPEX/TA	–0.039	–0.038	0.026	0.089	–0.069	0.014	0.537	1.000										
(9) R&D expenses/TA	–0.240	0.020	–0.139	0.128	0.408	–0.417	–0.155	–0.047	1.000									
(10) Tobin's Q	–0.017	0.119	–0.264	0.341	0.328	0.047	–0.117	0.023	0.242	1.000								
(11) Credit rating	0.155	0.174	–0.193	0.208	0.061	0.098	–0.008	–0.022	0.009	0.214	1.000							
(12) HHI	0.018	0.020	–0.019	–0.010	–0.067	0.071	–0.064	–0.078	–0.103	–0.009	0.099	1.000						
(13) Bank specialization	0.003	–0.040	0.029	–0.017	0.050	–0.095	0.088	0.095	0.106	0.008	–0.075	–0.157	1.000					
(14) Bank market share	0.477	0.025	0.066	–0.133	–0.092	0.096	0.067	–0.054	–0.137	0.013	0.112	0.080	–0.115	1.000				
(15) Bank concentration	0.054	0.039	–0.029	0.018	–0.007	0.042	–0.029	–0.077	–0.021	0.035	0.113	0.324	–0.134	0.209	1.000			
(16) Bank geographic diversification	0.196	0.027	0.002	–0.025	–0.035	0.042	–0.019	–0.049	–0.045	0.050	0.045	0.033	–0.248	0.330	0.054	1.000		
(17) Number of lending relationships	0.285	–0.014	0.116	–0.143	–0.105	0.032	0.059	–0.017	–0.090	–0.065	0.041	0.009	0.023	0.076	–0.048	–0.009	1.000	
(18) Lending relationship length	0.340	0.125	0.031	–0.063	–0.067	0.076	0.089	–0.055	–0.110	0.020	0.167	0.087	–0.028	0.305	0.124	0.125	0.059	1.000

Note: This table presents the correlations between the main variables used in our empirical analysis using U.S. data. Variable definitions are provided in Table A1 in Appendix. Our sample comprises yearly firm level data from U.S. firms borrowing in the syndicated loan market between 1996 and 2013.

Table O7. Summary statistics: Loan data

	N	Mean	Median	SD	P5	P95
Panel A: Belgian credit register data						
Cost of debt	142,037	0.16	0.07	0.25	0.01	0.84
ln(Loan amount)	168,587	12.28	12.55	2.45	8.23	15.44
Pr(Loan collateralized)	168,587	0.67	1.00	0.47	0.00	1.00
Pr(New long-term debt)	168,587	0.05	0.00	0.23	0.00	1.00
PD	168,587	0.03	0.01	0.09	0.00	0.09
Panel B: U.S. syndicated loan data						
ln(AISD)	13,969	4.77	4.92	0.84	3.22	5.89
ln(Loan amount)	15,452	4.91	5.01	1.69	1.79	7.60
Pr(Loan covenant violation)	5,046	0.36	0.12	0.40	0.00	1.00
ln(Loan maturity)	15,421	3.59	3.69	0.66	2.48	4.43

Note: This table presents summary statistics for the loan outcomes used in the analyses in Section 4.3. Panel A contains summary statistics for the loan outcomes from the Belgian credit register data. Panel B contains summary statistics for the loan outcomes from the U.S. syndicated loan data. Variable definitions are provided in Table A1 in Appendix.

Table O8. Bank specialization and loan conditions: Belgian credit register data

	(1) Cost of debt	(2) Pr(Loan collateralized)	(3) Pr(New long-term debt)	(4) ln(Loan amount)
Bank specialization$_{t-1}$	–0.14	0.01	0.03	4.86***
	(0.10)	(0.16)	(0.08)	(1.12)
Observations	142,037	168,587	168,587	168,587
Adjusted R-squared	0.45	0.18	0.03	0.21
Controls	Yes	Yes	Yes	Yes
Firm×Year FE	No	Yes	Yes	Yes
Bank×Year FE	No	Yes	Yes	Yes
Sector×Year FE	Yes	No	No	No
Firm FE	Yes	No	No	No

Note: This table shows the effect of bank specialization on borrowers' loan conditions depending. Across the different columns, the outcome variable is the ratio of interest expenses over total financial debt, a dummy variable equal to one for collateralized loans, a dummy variable equal to one for new long-term loan originations, and the natural logarithm of the total loan amount. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are double clustered at the bank and sector level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O9. Bank specialization and loan conditions: U.S. syndicated loan data

	(1) ln(AISD)	(2) Pr(Loan covenant violation)	(3) ln(Loan maturity)	(4) ln(Loan amount)
Bank specialization$_{t-1}$	0.10	–0.29*	0.28**	1.47***
	(0.14)	(0.16)	(0.12)	(0.24)
Observations	13,969	5,046	15,421	15,452
Adjusted R-squared	0.72	0.45	0.41	0.78
Controls	Yes	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on borrowers' loan conditions. Across the different columns, the outcome variable is the natural logarithm of the all-in-drawn-spread, loan covenant strictness, the natural logarithm of loan maturity, and the natural logarithm of the total loan amount. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are double clustered at the bank and sector level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O10. Robustness: U.S. data sample: Controlling for interactions between asset overhang and other bank characteristics

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.45	0.62	0.43	0.60
	(0.57)	(0.65)	(0.38)	(0.47)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.70**	–1.11**	–1.61***	–0.78*
	(0.70)	(0.56)	(0.50)	(0.41)
Bank concentration$_{t-1}$	–0.38	–2.08***	–0.30	–0.82*
	(0.26)	(0.57)	(0.25)	(0.45)
Bank concentration$_{t-1}$ × Asset overhang$_{t-1}$	–0.41	1.45***	0.27	0.64*
	(0.38)	(0.44)	(0.31)	(0.35)
Bank market share$_{t-1}$	0.34	0.44	0.24	0.30
	(0.28)	(0.44)	(0.25)	(0.35)
Bank market share$_{t-1}$ × Asset overhang$_{t-1}$	–0.51	–0.16	–0.71***	–0.28
	(0.42)	(0.37)	(0.27)	(0.29)
Bank geographic diversification$_{t-1}$	0.51**	0.31	–0.00	–0.06
	(0.23)	(0.36)	(0.18)	(0.24)
Bank geographic diversification$_{t-1}$ × Asset overhang$_{t-1}$	–0.15	0.11	–0.03	0.05
	(0.34)	(0.29)	(0.22)	(0.19)
Lending relationship length$_{t-1}$	0.00	–0.01	–0.02	–0.02
	(0.01)	(0.02)	(0.01)	(0.01)
Lending relationship length$_{t-1}$ × Asset overhang$_{t-1}$	0.02	0.02	0.01	0.00
	(0.02)	(0.01)	(0.01)	(0.01)
Number of lending relationships$_{t-1}$	0.01	0.03	–0.06**	–0.05
	(0.03)	(0.06)	(0.03)	(0.05)
Number of lending relationships$_{t-1}$ × Asset overhang$_{t-1}$	0.03	–0.01	0.10**	0.02
	(0.06)	(0.04)	(0.05)	(0.03)
Observations	24,209	24,209	24,035	24,035
Pseudo R-squared	0.72	0.72	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates, while controlling for interactions between asset overhang and other bank characteristics. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O11. Robustness: U.S. data sample: Fixed effects

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Including firm fixed effects				
Bank specialization$_{t-1}$	–0.31	–0.24	0.32	0.22
	(0.38)	(0.36)	(0.50)	(0.47)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.90**	–1.39***	–1.07**	–1.09**
	(0.38)	(0.36)	(0.52)	(0.44)
Observations	9,923	9,923	9,787	9,787
Adjusted R-squared	0.73	0.73	0.43	0.43
Panel B: Including bank-by-time fixed effects				
Bank specialization$_{t-1}$	0.93	1.54	–0.43	–0.23
	(0.90)	(1.03)	(0.64)	(0.68)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.63*	–1.48**	–1.39**	–0.69
	(0.95)	(0.75)	(0.63)	(0.46)
Observations	14,003	14,003	13,847	13,847
Pseudo R-squared	0.76	0.76	0.41	0.41
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. Panel A includes firm fixed effects. Panel B includes bank-by-time fixed effects using the sample of firms with a single (lead arranger) bank relationship. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O12. Bank specialization, asset overhang, and corporate innovation: U.S. data sample:

	Patent generality		Patent originality	
	(1)	(2)	(3)	(4)
Panel A: Baseline				
Bank specialization$_{t-1}$	0.03	0.03	0.05*	0.04
	(0.04)	(0.04)	(0.03)	(0.03)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.08***	–0.08*	–0.05***	–0.04*
	(0.03)	(0.04)	(0.02)	(0.03)
Observations	31,915	31,915	31,915	31,915
Adjusted R-squared	0.38	0.38	0.36	0.36
Panel B: Including firm fixed effects				
Bank specialization$_{t-1}$	0.13	0.10	0.16**	0.14*
	(0.11)	(0.11)	(0.07)	(0.07)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.28***	–0.17*	–0.21***	–0.15**
	(0.09)	(0.09)	(0.06)	(0.06)
Observations	9,923	9,923	9,923	9,923
Adjusted R-squared	0.20	0.20	0.20	0.20
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the generality of the patents filed by a firm in a given year. In the last two columns, the outcome variable is the originality of patents filed by a firm in a given year. Across the different columns, we use two distinct measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.2. In Panel A, we include the entire baseline sample. In Panel B, we restrict the sample to firms that filed at least one patent over the sample period. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O13. Robustness: U.S. data sample: Alternative measures of bank specialization

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Bank specialization based on number of lending relationships				
Bank specialization$_{t-1}$	0.77	1.37	0.44	0.74
	(0.90)	(1.01)	(0.61)	(0.71)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.38	–1.48*	–1.98***	–1.02*
	(1.08)	(0.84)	(0.75)	(0.59)
Observations	24,209	24,209	24,035	24,035
Adjusted R-squared	0.71	0.71	0.36	0.36
Panel B: Bank specialization based on 3-digit SIC codes				
Bank specialization$_{t-1}$	0.37	0.65	0.57	0.47
	(0.79)	(0.84)	(0.47)	(0.49)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–2.40***	–2.27***	–0.98**	–0.21
	(0.87)	(0.75)	(0.45)	(0.42)
Observations	18,826	18,826	18,667	18,667
Pseudo R-squared	0.84	0.84	0.38	0.38
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. In Panel A, bank specialization is computed as the fraction of the number of borrowers that a bank has in a given sector relative to the total number of borrowers that a bank has in its entire loan portfolio in a given year. In Panel B, bank specialization is computed as the share of credit granted by a bank to the firms in a given sector relative to the bank's total credit granted, where sectors are defined using 3-digit instead of 2-digit SIC codes. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O14. Robustness: U.S. data sample: Alternative lead arranger definitions

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Bank specialization based on lead arranger definition from Ivashina (2009)				
Bank specialization$_{t-1}$	0.49	1.14**	0.31	0.66*
	(0.49)	(0.55)	(0.32)	(0.39)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.92**	–1.50***	–2.03***	–0.84**
	(0.83)	(0.48)	(0.53)	(0.35)
Observations	26,028	26,028	25,854	25,854
Adjusted R-squared	0.70	0.70	0.36	0.36
Panel B: Bank specialization based on lead arranger's exact loan share				
Bank specialization$_{t-1}$	0.74	1.22*	0.42	0.69
	(0.58)	(0.65)	(0.38)	(0.44)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.53**	–1.54***	–1.68***	–0.90**
	(0.75)	(0.60)	(0.50)	(0.39)
Observations	24,716	24,716	24,542	24,542
Pseudo R-squared	0.72	0.72	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. In Panel A, bank specialization is computed as the share of credit granted by a bank to the firms in a given sector relative to the bank's total credit granted, where lead arrangers are defined based on the definition of Ivashina (2009) instead of Chakraborty, Goldstein, and MacKinlay (2018). In Panel B, bank specialization is computed as the share of credit granted by a bank to the firms in a given sector relative to the bank's total credit granted, where lead arrangers are attributed their exact loan share instead of the entire loan amount of the syndicate. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O15. Robustness: U.S. data sample: Excluding bank-sector-time bins with less than ten loans or without assuming that loans remain "active"

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Excluding bank-sector-time bins with less than ten loans				
Bank specialization$_{t-1}$	0.34	0.88	–0.05	0.33
	(0.76)	(0.88)	(0.53)	(0.58)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–2.05**	–1.87**	–1.94***	–1.32***
	(0.93)	(0.74)	(0.58)	(0.50)
Observations	19,931	19,931	19,791	19,791
Pseudo R-squared	0.74	0.74	0.37	0.37
Panel B: Bank specialization based on loans *granted* in year t				
Bank specialization$_{t-1}$	0.29	0.69	0.33	0.43
	(0.58)	(0.79)	(0.31)	(0.31)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.81***	–1.16**	–1.08**	–0.37*
	(0.56)	(0.59)	(0.43)	(0.22)
Observations	24,209	24,209	24,035	24,035
Pseudo R-squared	0.73	0.73	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. In Panel A, bank specialization is computed as the share of credit granted by a bank to the firms in a given sector relative to the bank's total credit granted, where bank-sector-time bins with less than then loans are excluded from the sample. In Panel B, bank specialization is computed based only on loans originated in year t (without assuming that loans remain "active" after origination). Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O16. Robustness: U.S. data sample: Excluding recession periods or multiple-bank borrowers

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Excluding recession periods				
Bank specialization$_{t-1}$	0.22	0.68	0.41	0.61
	(0.58)	(0.66)	(0.39)	(0.47)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.43*	–1.24**	–1.52***	–0.71*
	(0.74)	(0.56)	(0.50)	(0.39)
Observations	20,293	20,293	20,119	20,119
Pseudo R-squared	0.72	0.72	0.36	0.36
Panel B: Excluding multiple-bank borrowers				
Bank specialization$_{t-1}$	0.34	0.67	0.27	0.53
	(0.65)	(0.75)	(0.41)	(0.49)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.49**	–1.02	–1.52***	–0.73*
	(0.75)	(0.64)	(0.51)	(0.42)
Observations	14,716	14,716	14,580	14,580
Pseudo R-squared	0.74	0.74	0.37	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. In Panel A, recession periods (as defined by the NBER Business Cycle Dating Committee) are excluded from the sample. In Panel B, multiple-bank borrowers are excluded from the sample. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O17. Robustness: U.S. data sample: Alternative clustering methods

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Standard errors clustered by sector				
Bank specialization$_{t-1}$	0.38	0.88	0.42	0.65
	(0.77)	(0.98)	(0.34)	(0.41)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.51**	–1.38**	–1.53***	–0.81**
	(0.66)	(0.65)	(0.52)	(0.36)
Observations	24,209	24,209	24,035	24,035
Pseudo R-squared	0.71	0.71	0.36	0.36
Panel B: Standard errors clustered by bank				
Bank specialization$_{t-1}$	0.34	0.67	0.27	0.53
	(0.47)	(0.58)	(0.39)	(0.43)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–1.49**	–1.02	–1.52***	–0.73**
	(0.66)	(0.72)	(0.39)	(0.28)
Observations	14,716	14,716	14,580	14,580
Pseudo R-squared	0.74	0.74	0.37	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. Variable definitions are provided in Table A1 in Appendix. In Panel A, standard errors are clustered at the sector level instead of the firm level. In Panel B, standard errors are clustered at the bank level instead of the firm level, using the sample of firms with a single (lead arranger) bank relationship. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O18. Robustness: U.S. data sample: OLS estimation

	ln(1+patents)		ln(1+citations)	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.24*	0.21	0.08	0.06
	(0.13)	(0.13)	(0.11)	(0.11)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	–0.34***	–0.31**	–0.22***	–0.20*
	(0.11)	(0.13)	(0.08)	(0.11)
Observations	31,915	31,915	31,915	31,915
Adjusted R-squared	0.42	0.42	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the natural logarithm of one plus the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the natural logarithm of one plus the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. The results are estimated using OLS instead of Poisson fixed effects estimation. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O19. Robustness: U.S. data sample: Alternative empirical specification

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}^{Low\ asset\ overhang}$	2.32***	2.87***	1.35**	1.43**
	(0.76)	(0.93)	(0.52)	(0.65)
Bank specialization$_{t-1}^{High\ asset\ overhang}$	–1.47*	–1.22*	–0.86*	–0.54
	(0.86)	(0.74)	(0.50)	(0.41)
Observations	24,209	24,209	24,035	24,035
Adjusted R-squared	0.77	0.77	0.36	0.36
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes	Yes
State×Year FE	Yes	Yes	Yes	Yes

Note: This table shows the effect of bank specialization on firms' innovation output depending on the asset overhang of the sector in which a firm operates. In the first two columns, the outcome variable is the number of patents filed by a firm in a given year. In the last two columns, the outcome variable is the average number of forward-citations received by the patents filed by a firm in a given year. Across the different columns, we use different measures of asset overhang, as indicated at the bottom of the table. The measures of asset overhang are described in Section 3.3. Variable definitions are provided in Table A1 in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

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