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Bank Specialization and Corporate Innovation

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Abstract

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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. For example, bank competition and lending relationships have been shown to have a positive effect on firms' innovation activities (Cornaggia et al., 2015; Herrera and Minetti, 2007), while zombie lending has been shown to have a negative effect (Schmidt et al., 2023). Despite these contributions, no research has studied the role of bank specialization, which is the notion that banks concentrate their lending disproportionately in specific sectors (Blickle et al., 2023; Paravisini et al., 2023). This research gap is surprising, not only because bank specialization is a defining feature of banks' business model, but also because the effect of bank specialization on corporate innovation is theoretically ambiguous. To address this gap in the literature, this paper uses unique data to study how bank specialization affects firms' innovation activities and the potential mechanisms underlying this effect.

On the one hand, bank specialization enables banks to develop sector-specific expertise, which improves their screening and monitoring capabilities (Blickle et al., 2023; He et al., 2023). Given that innovation requires investments in opaque, risky assets (Hall and Lerner, 2010; Rajan and Zingales, 1998), specialized banks may be more inclined to support firms' innovation activities. On the other hand, research has shown that the innovation activities of one firm can adversely affect other firms, for instance through business stealing (e.g., Aghion and Howitt, 1992; Bloom et al., 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. Thus, ultimately, whether and how bank specialization affects corporate innovation is an empirical question.

To address this question, we use two unique and complementary datasets. Our first dataset combines U.S. syndicated loan data with patent data. The U.S., being one of the leading patenting countries in the world, has been widely used to study firms' innovation activities (Hall and Lerner, 2010). In addition, syndicated loan data, which contains detailed information on firm-bank relationships and loan conditions, has been commonly used to analyze how bank lending policies affect real firm outcomes (Ivashina and Scharfstein, 2010;

Saidi and Streitz, 2021). A potential limitation of our U.S. dataset, however, is that it only covers certain types of innovation output (i.e., patented innovations) and certain types of firms (i.e., large, typically listed firms). To resolve this, we employ a second dataset that combines micro-level innovation survey data administered by the European Commission and credit register data from a representative European country (Belgium). This dataset covers all types of innovations irrespective of whether those innovations are (ultimately) patented, and many small (private) firms that are heavily dependent on bank credit with limited access to other types of financing.

We start with the U.S. data sample and analyze how the sectoral specialization of a firm's lender affects the different dimensions of a firm's patent output. Following previous papers, we measure a bank's sectoral specialization as the share of the bank's loan portfolio in a specific sector relative to the bank's entire loan portfolio (e.g., De Jonghe et al., 2024; Iyer et al., 2022). Further, following prior literature, we use the number of patents that a firm files to capture the quantity of a firm's innovation output, and the number of citations that a firm's patents receive from future patent applications to capture the quality or economic impact of a firm's innovation output (Aghion et al., 2005; Hall et al., 2001, 2005).

We find that, on average, bank specialization has a statistically insignificant effect on the quantity and quality of firms' patent output. Interestingly, we show that this insignificant result is not due to the fact that bank specialization does not affect corporate innovation, but due to the fact that, on average, our two theoretical predictions offset each other.

To show the latter, we identify conditions under which only one of the two mechanisms described above prevails. Particularly, we exploit heterogeneity in "asset overhang" across sectors, i.e., the risk that a new technology adversely affects the value of a bank's legacy loan portfolio (Degryse et al., 2023).[1] The reasoning is that, in sectors with low asset overhang we would expect the positive effect to prevail, while in sectors with high asset overhang we would expect the negative effect to prevail. We therefore build on prior literature and construct two distinct measures of asset overhang. First, we use a measure of asset redeployability

[1]Note that the asset overhang problem proposed by Degryse et al. (2023) 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.

constructed by Kim and Kung (2017), which captures the extent to which the assets used in a certain sector can be redeployed within and across sectors. Second, we use a measure of product market rivalry developed by Bloom et al. (2013), which is based on a sales-weighted average of competitor firms' R&D stock. The first measure captures the extent to which a new technology could adversely affect the value of a firm's pledged collateral, while the second measure captures the extent to which a new technology could adversely affect firm value through business stealing, and thereby cover the two main mechanisms through which new technologies can impose externalities on existing technologies (Aghion and Howitt, 1992).

Using each of these measures, we extend our baseline regression model by adding an interaction term between a lender's sectoral specialization and the asset overhang of the sector in which a firm operates. Based on this, we find that the sign and magnitude of the effect of bank specialization on corporate innovation varies depending on the underlying asset overhang. Our results show that, in sectors with low asset overhang, borrowing from a specialized bank has a positive effect on firms' innovation output. More precisely, in sectors with high asset redeployability and low product market rivalry, bank specialization is associated with an increase in firms' patent quantity and quality. In contrast, in sectors with high asset overhang, our results show that borrowing from a specialized bank has a negative effect on firms' innovation output. These effects are statistically and economically significant. For instance, in sectors with low (high) asset overhang, a one standard deviation increase in bank specialization is ceteris paribus associated with a 10–15% increase (decrease) in the number of patents and patent citations.

We find very similar results based on the novelty (or nature) of firms' innovation output. To this end, we follow the innovation literature and use the originality and generality of patents to distinguish between incremental and radical innovation (Trajtenberg et al., 1997). Radical innovation tends to be more risky and influential than incremental research, which is reflected through higher values of patent originality and generality. In line with our previous results, we find that the effect of bank specialization on patent novelty is positive in sectors with low asset overhang and negative in sectors with high asset overhang. Thus, bank specialization does not only affect firms' patent quantity and quality, but also firms' patent novelty, which is an important insight considering that radical innovation is the key driver of long-term economic growth (Acemoglu, 2008).

We then turn to our second dataset, which combines Belgian credit register data with innovation survey data from the Belgian input to the Community Innovation Survey (CIS) administered by the European Commission. As mentioned earlier, this dataset complements our U.S. data sample in two ways; (i) the CIS covers all types of innovations, including non-patented ones, and (ii) the CIS covers many small (private) firms that are heavily bank-dependent, face large switching costs, and have limited access to other types of financing (such as private equity or venture capital). Using the CIS data, we study firms' probability to introduce product innovations, process innovations, and world-first innovations. This means that, as in our analysis based on patenting, we capture both the quantity and quality (or novelty) of firms' innovation output.

Consistent with our earlier findings, we find that, on average, bank specialization does not affect firms' innovation output. However, our results again indicate that the effect depends on the asset overhang of the sector in which a firm operates. We find that bank specialization increases the probability that firms develop product innovations and world-first innovations in sectors with low asset overhang, while the opposite holds in sectors with high asset overhang. The innovation survey evidence thus shows that the heterogeneous effects of bank specialization are not confined to large firms or patent innovations, highlighting the external validity of our findings.

These results also hold for a battery of robustness checks. First, we show that our results hold using exogenous variation in bank specialization to mitigate potential concerns that the endogeneity of lenders' sectoral specialization may bias our baseline results. In particular, we follow previous studies and use mergers between banks active in the syndicated loan market as a source of exogenous variation in bank specialization (Iyer et al., 2022; Saidi and Streitz, 2021). We then 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. Using this approach, we provide evidence that our baseline findings hold. In addition, to further mitigate potential endogeneity concerns, we draw on the approach of Foà et al. (2019)

and show that there is no endogenous matching between more (less) innovative firms with more (less) specialized banks in sectors with low (high) asset overhang.

Second, we show that it is unlikely that our results are driven by other channels. One potential concern is that our results are due to the fact that bank specialization reduces zombie lending (De Jonghe et al., 2024), which could in turn increase corporate innovation (Schmidt et al., 2023). Another potential concern is that our results are due to banks' technological conservatism, which refers to the idea that banks may impede innovation because they are reluctant to learn about new technologies (see Minetti, 2011). We rule out these alternative channels by showing that our results hold when we control for banks' sectoral zombie lending, and when we control for an interaction term between our measure of bank specialization and a sector level measure of informational complexity (the idea being that technological conservatism would be more relevant for firms operating in informationally complex sectors).

Third, to further mitigate concerns about omitted variable bias, we show that interaction terms between asset overhang and other bank characteristics—such as banks' market share or bank competition—are statistically insignificant, thereby confirming the relevance of the channel that we document. Further, to rule out that our results are driven by unobserved firm- or bank-specific characteristics that could be correlated with bank specialization, we show that our results hold when we include firm or bank-by-time fixed effects. The former essentially restrict our sample to firms that patent at least once over the sample period and, hence, an intensive margin effect. The latter control for any bank-specific time-varying unobserved heterogeneity that could jointly influence banks' specialization and lending decisions.

Fourth, we show that our results hold using alternative measures of bank specialization. A potential limitation of our baseline measure is that specialization in a certain sector could be driven by a few large borrowers, which would limit the scope of learning through repeated lending and the scope of technology-induced spillovers on bank's legacy loan portfolio. To address this, we show that our results hold if we measure bank specialization as the ratio of a bank's number of borrowers in a given sector relative to the bank's total number of borrowers. Further, we show that our results hold if we compute bank specialization based on 3-digit instead of 2-digit SIC codes. Finally, we provide a series of tests showing that our results are robust to alternative empirical specifications, sub-samples, or measurement choices.

In the last part of our paper, we investigate the potential mechanism underlying our findings. Following prior studies in the field of banking and innovation, we focus on the traditional role of banks as financiers of firms' investments (Amore et al., 2013; Granja and Moreira, 2023; Herrera and Minetti, 2007).[2] Specifically, we investigate how lenders' sectoral specialization affects borrowers' loan conditions, and whether this effect depends on the innovativeness and the asset overhang of the sector in which borrowers operate. In doing so, we focus on the contractual loan rate, loan maturity, and loan covenants, which are three key loan terms that can influence firms' investments in innovative projects. For instance, loan maturities affect firms' refinancing risk and propensity to invest in long-term projects (Aghion et al., 2010; Diamond, 1991, 1993), while covenants influence firms' financial and operational flexibility to invest in risky projects (Chava and Roberts, 2008; Nini et al., 2009).

We find that banks generally offer more favorable loan terms to firms operating in sectors in which they are specialized, which is consistent with previous studies (Blickle et al., 2023; Giometti et al., 2022). For instance, our results show that, on average, firms borrowing from specialized banks receive loans with larger loan amounts, longer loan maturities, and less restrictive debt covenants than firms borrowing from non-specialized banks. However, this does not hold for borrowers operating in more innovative sectors with high asset overhang. First, we find that those borrowers are charged higher loan rates, suggesting that specialized banks require a risk premium for their exposure to technology-induced spillovers. Second, those borrowers receive loans with shorter (instead of longer) maturities and more (instead of less) restrictive covenants if they borrow from specialized banks, which constrains (instead of promotes) their propensity to invest in long-term, risky projects. For example, on average, a one standard deviation increase in bank specialization is associated with a 6% decrease in firms' debt covenant strictness but, for firms operating in innovative sectors with high asset overhang, a one standard deviation increase in bank specialization is associated with a 10% increase in debt covenant strictness. These results suggest that banks are aware of and

[2] Several studies have shown that financing conditions are an important channel through which banks can affect firms' investments, including investments in innovative projects. For instance, banks can directly influence firms' investments through loan maturities (Diamond, 1991, 1993; Johnson, 2003) and loan covenants (Chava and Roberts, 2008; Nini et al., 2009).

internalize the potential negative spillovers of new technologies on their legacy loan portfolios, which in turn influences firms' financing conditions and innovation activities.

In sum, our paper shows that bank specialization affects corporate innovation, and that the sign and magnitude of this effect depend on the asset overhang of the sector in which a firm operates. In sectors with high asset overhang, bank specialization enhances firms' innovation activities, while in sectors with low asset overhang, bank specialization impedes firms' innovation activities. This finding underscores the dual facets of bank specialization (Iyer et al., 2022) and highlights how product market characteristics can serve as financial frictions that constrain banks' potential to spur corporate innovation.

Our paper contributes to several strands of literature. First, our paper contributes to the large literature on finance and innovation (for an overview, see Hall and Lerner, 2010; Kerr and Nanda, 2015). Despite the importance of venture capital financing for innovative firms, there is growing evidence that bank credit plays an important role in financing innovation (e.g., Hochberg et al., 2018; Kerr and Nanda, 2015; Robb and Robinson, 2014). Consequently, several studies have examined how credit supply shocks stemming from changes in the structure of the banking sector affect firms' innovation activities (Amore et al., 2013; Benfratello et al., 2008; Bircan and De Haas, 2020; Chava et al., 2013; Cornaggia et al., 2015; Deng et al., 2021; Granja and Moreira, 2023; Nanda and Nicholas, 2014). These studies generally find that increased access to bank credit raises firms' innovation activities. Other studies have also examined how lending relationships (Herrera and Minetti, 2007; Hombert and Matray, 2017) or banks' zombie lending (i.e., banks' lending to non-viable firms that would otherwise exit the economy, see Schmidt et al., 2023) affect firms' innovation activities. We contribute to this literature by studying how bank specialization affects corporate innovation and, thus, economic growth.

Second, our paper contributes to the literature on the interaction between financial and product markets (for an overview, see Frésard and Phillips, 2024). Our paper primarily relates to papers that study the financial frictions that influence banks' incentives to finance firms' innovation activities (Atanassov, 2016; Araujo et al., 2019; Cerqueiro et al., 2017; Degryse et al., 2023; Minetti, 2011; Saidi and Žaldokas, 2021). We add to these papers by showing that interactions between banks' business model and product market characteristics—such as product market rivalry and asset redeployability—influence banks' incentives to finance firms' innovation activities. More broadly, our results contribute to recent findings from López and Vives (2019) and Antón et al. (2023), who show that the effect of common ownership on corporate innovation can be positive or negative depending on the relative strength of technology and product market spillovers, by extending it to bank specialization.

Our paper therefore also contributes to the literature on the effects of bank specialization. Recent empirical evidence has shown that banks specialize by concentrating their loan portfolios in specific sectors (Acharya et al., 2006; Blickle et al., 2023).[3] Previous papers have argued that this allows banks to develop sector-specific expertise which reduces their screening and monitoring costs (He et al., 2023), and thereby enables them to offer more favorable loan conditions (Blickle et al., 2023; Cao et al., 2023; Giometti et al., 2022). In addition, De Jonghe et al. (2024) find that bank specialization reduces zombie lending as specialized banks are better informed about the presence of zombie firms and the corresponding negative spillovers on healthy firms. Further, focusing on the potential spillover effects of bank specialization, Iyer et al. (2022) and Paravisini et al. (2023) find that bank specialization plays an important role in the propagation of shocks to the real economy.

We add to this literature by studying the effect of bank specialization on firms' innovation activities, an important channel through which bank specialization could affect economic growth. Our paper shows that this effect can be positive or negative, depending on the underlying asset overhang, and thereby highlights the dual facets of bank specialization (Iyer et al., 2022). Specifically, we show that bank specialization improves innovation for firms operating in sectors with low asset overhang, while the opposite holds in sectors with high asset overhang. In general, the latter finding is consistent with the asset overhang channel proposed by Degryse et al. (2023), which states that a bank may impede the development of new technologies in case those technologies could have negative spillover effects on its legacy loan portfolio. We further show that the mechanism underlying our results is related to banks'

[3] While we focus on banks' sectoral specialization, there is also a growing literature on banks' geographical specialization (Casado and Martinez-Miera, 2023; Doerr and Schaz, 2021; Duquerroy et al., 2022; Gelman et al., 2023).

traditional role as financiers of firms' investments (Deng et al., 2021; Herrera and Minetti, 2007). Specifically, we show that firms generally obtain more favorable loan conditions from specialized banks, but this does not hold for firms operating in innovative sector with high asset overhang. This suggests that the effects of bank specialization on corporate innovation is related to the effect of bank specialization on firms' financing conditions which, in turn, influences firms' investments in innovation activities.

2. Theoretical Background

In this section, we elaborate on the theoretical predictions about the effect of bank specialization on firms' innovation output.

On the one hand, one could argue that bank specialization would benefit corporate innovation. This argument builds on the idea that bank specialization enables banks to develop sector-specific expertise, which improves their screening and monitoring capabilities (Blickle et al., 2023; He et al., 2023). Given that innovation requires investments in informationally opaque, risky assets (Hall and Lerner, 2010; Herrera and Minetti, 2007; Rajan and Zingales, 2001), specialized banks may be more inclined to support firms' innovation activities. This implies that bank specialization could improve corporate innovation. In sum, our first hypothesis (H1) can be formally stated as follows:

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

This positive effect could however be mitigated by the fact that new technologies can adversely affect existing technologies, a problem that is particularly relevant for specialized banks. More specifically, the Schumpeterian view of growth and "creative destruction" (Schumpeter, 1943) posits that new technologies can render existing goods, markets, and manufacturing processes obsolete, for instance through business stealing or a devaluation of pledged collateral (Aghion and Howitt, 1992, 1998; Aghion et al., 2015; Bloom et al., 2013).[4] In line with this idea, Bloom et al. (2013) show that, for firms that operate closely in

[4] Kodak is a good example of a firm whose product became obsolete due to technological change. In the 1980s and the 1990s, Kodak was the leading producer of films for cameras and one of the most active patenting firms in the United States. 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

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 Argente et al., 2024; Jaffe, 1986; Ma, 2021; Utterback, 1994).

Building on this idea, Degryse et al. (2023) extend the theoretical model from Holmstrom and Tirole (1997) to study the influence of such technology-driven spillovers on banks' incentive to fund innovative projects. They show that the composition of a bank's legacy portfolio can affect its decision to fund new, innovative projects if these projects could have negative spillovers on the value of the bank's legacy portfolio. Consequently, to preserve the value of the existing technologies underlying its legacy portfolio, a bank may decide not to fund a firm's (disruptive) innovative projects or, more generally, to impede innovation (also see Becker and Ivashina, 2023).[5] Degryse et al. (2023) refer to this as the asset overhang problem, a problem that is particularly relevant for specialized banks. The reason for this is that technology-induced shocks resulting from the innovation activities of one firm primarily affect other firms operating in the same sector, and specialized banks are more exposed to the potential impact of such shocks because their legacy portfolios are disproportionately concentrated in specific sectors. Thus, banks' incentive to impede the development of new technologies could be an increasing function of their sectoral specialization.

Importantly, this incentive will only apply if new technologies could adversely affect existing technologies, which is not necessarily the case. For instance, while Bloom et al. (2013) show that new technologies can have negative spillover effects for firms that operate closely in product market space, they also show that new technologies can have positive spillover effects for firms that operate closely in technology space (also see Bernstein and Nadiri, 1989; Jaffe, 1986; Kogan et al., 2017). In general, the risk that a new technology would adversely affect the value of (the existing technologies underlying) a bank's legacy portfolio can occur through two mechanisms, namely (1) a reduction in firm value due to a

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).

[5] In line with this idea, Becker and Ivashina (2023) show that disruptive innovation can increase incumbent firms' default risk.

decrease in the value of the firm's pledged collateral, and (2) a reduction in firm value due to reduced firm performance (e.g., through business stealing) (Aghion and Howitt, 1992; Becker and Ivashina, 2023; Bloom et al., 2013). Using the terminology from Degryse et al. (2023), we will refer to the risk underlying these mechanisms as asset overhang. Based on this, we posit that bank specialization could impede the innovation activities of firms operating in sectors with high asset overhang, and improve the innovation activities of firms operating in sectors with low asset overhang. Formally, our second hypothesis (H2) can be stated as follows:

H2: Bank specialization has a positive effect on the innovation output of firms in sectors with low asset overhang, and a negative effect on the innovation output of firms in sectors with high asset overhang.

3. Data and Measurement

This section defines the main variables used in our empirical analysis, their data sources, and summary statistics. Our main analysis is based on U.S. syndicated loan data combined with patent data. The data and methodology used in our analysis based on Belgian credit register data combined with innovation survey data is explained in detail in Section 5.1.1.

3.1. Measuring bank specialization

We construct our independent variable of interest at the bank-sector-year level, where sectors are based on 2-digit SIC classification. Following prior literature (e.g., De Jonghe et al., 2024; Iyer et al., 2022), we define a bank's sectoral specialization as the ratio of outstanding credit from bank b to sector s at time t relative to the bank's total credit:

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

where $Credit_{b,f,s,t}$ is the credit from bank b to firm f operating in sector s at time t. F^s corresponds to the total number of firms in sector s and S to the the total number of sectors. Bank specialization captures the importance of a sector in a bank's loan portfolio and ranges from zero (no lending to a sector) to one (absolute specialization in a sector). In robustness tests, discussed below, we show that our results hold using alternative measures of bank specialization, including a measure based on 3-digit (instead of 2-digit) SIC codes and a measure based on the number of lending relationships (instead of the amount of credit granted).[6]

3.2. Measuring corporate innovation

To measure corporate innovation, we follow the innovation literature and focus on the quantity, quality, and novelty of firms' patents (e.g., Chava et al., 2013; Nanda and Nicholas, 2014). Before we elaborate on these measures, it is worth highlighting that the use of patents has at least three important advantages over the use of R&D expenditures as a measure of innovation (Atanassov, 2016). First, R&D expenditures capture research input, while patents capture research output. Second, unlike R&D expenditures, patents allow to capture the quality and novelty of corporate innovation. Third, unlike R&D expenditures, patents are not sensitive to accounting norms (such as whether they should be capitalized or expensed). As a result, patents have become the most widely accepted method used to measure technological change.

The first innovation measure used in our analysis is the number of patents filed (that were eventually granted) by a firm f in year t, which captures the quantity of a firm's innovation output. As is common in the literature, we use the application year instead of the grant year of the patents as the former is closer to the time of the actual invention (Hall et al., 2001).

The second innovation measure used in our analysis is the average number of citations that a firm's patents receive from future patent applications in subsequent years. This measure captures the quality of a firm's innovation output as patents that have more citations are typically interpreted as having more scientific and economic impact.[7] In line with this idea, Hall et al. (2005) for instance show that there is a positive relationship between patent citations and firm value (also see Kogan et al., 2017). Following prior literature, we use the number of citations received during the first five years after a patent was granted.[8]

[6] Our data sample used to compute bank specialization is based on approximately 33,000 loan packages and 48,000 loan facilities. On average, a bank-sector-time bin has 52 underlying loan facilities. Robustness tests, discussed below, show that our results hold if we drop bank-sector-time bins with less than ten underlying loan facilities.

[7] 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.

[8] To mitigate potential concerns about truncation bias, unreported results confirm that our results are robust to using the

The third innovation measure used in our analysis is patent novelty. Previous papers have argued that, while the number of patent citations reflects scientific and economic impact, it cannot accurately capture whether an innovation is incremental or radical (break-through). This distinction is important as radical research tends to be more risky and influential than incremental research. In addition, radical research is more important for long-term economic growth (Acemoglu, 2008; Caggese, 2019). To distinguish between incremental and radical innovation, we follow the innovation literature and use the originality and generality of patents as measures of patent novelty (Trajtenberg et al., 1997). Patent originality captures the breadth of the technological fields that a patent relies on or, put differently, the knowledge diversity behind a patent. Patent originality is computed as $1-\sum_{j=1}^{N_j} b_{ij}^2$ where b_{ij} denotes the ratio of the number of cited patents belonging to technology class j to the number of patents cited by patent i. N_j represents the number of distinct patent technology classes, which are defined using the International Patent Classification (IPC) system to classify the content of patents. A patent has a high value of originality if it cites prior patents from many different technology classes, meaning that the patent recombines a broader set of prior art. Patent generality captures the breadth of the technological fields of later generations of innovations that benefit from a patent. Patent generality is computed as $1-\sum_{j=1}^{N_j} f_{ij}^2$ where f_{ij} denotes number of patents citing patent i belonging to technology class j scaled by the number of patents citing patent i. N_j represents the number of distinct patent technology classes. A patent has a high value of generality if it is cited by patents from many different technology classes, meaning that the patent has a broader impact or is more generally applied.

3.3. Measuring asset overhang

We construct two measures of asset overhang, which captures the risk that a new technology adversely affects the value of a bank's legacy loan portfolio (Degryse et al., 2023).[9] In doing so, we focus on the two main dimensions through which new technologies can adversely affect

number of citations received during the first seven years after a patent was granted. In addition, to mitigate concerns about technological fluctuations (see Hall et al., 2001; Lerner and Seru, 2022), unreported results show that our results are robust to adjusting the number of patent and patent citations using the technology class-year adjustment outlined by Hall et al. (2001).

[9]As mentioned before, the asset overhang problem proposed by Degryse et al. (2023) 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.

the value of (the existing technologies underlying) a bank's legacy loan portfolio, namely (1) a reduction in firm value due to a devaluation of the firm's pledged collateral, and (2) a reduction in firm value due to reduced firm performance (e.g., through business stealing) (Aghion and Howitt, 1992; Bloom et al., 2013; Schumpeter, 1943; Utterback, 1994).

First, we create a measure of asset redeployability proposed by Kim and Kung (2017). This measure is constructed based on data from the 1997 Bureau of Economic Analysis capital flows table, which contains investments (capital expenditures) for 123 sectors across 180 asset categories. First, Kim and Kung (2017) compute an asset level redeployability score for each asset category as the percentage of the sectors using that asset. Note that, an important advantage of this asset level redeployability score is that it captures the extent to which an asset has alternative uses both *within* and *across* sectors.[10] Then, for each sector, the authors calculate the sector-year level average of the category level asset redeployability scores (where the weights are given by each asset category's percentage of total sector capital expenditures), resulting in a sector-year level asset redeployability score. Since redeployable assets are sold more actively in secondary markets and more easily transferable to other sectors, the collateral devaluation from an adverse (technological-driven) shock would be smaller for firm operating in sectors with more redeployable assets (Benmelech, 2009; Benmelech and Bergman, 2009). Consequently, sectors with high asset redeployability have lower asset overhang.

Second, we use a measure of product market rivalry pioneered by Bloom et al. (2013). This measure is computed as the R&D stock of a firm's rivals aggregated by pairwise spatial closeness in product market space, where closeness in product market space is proxied based on the distribution of the firm's sales across sectors. A detailed discussion of this measure (and its micro-economic foundations) is provided by Bloom et al. (2013) but, in essence, this measure quantifies a firm's exposure to technology-induced competition from rivals' innovation activities. We aggregate this measure to create a sector-year level measure of product market rivalry. The reasoning behind this measure is that firms operating in sectors with higher product market rivalry are more exposed to business stealing effects (and hence risk losing a

[10]The asset categories include, among others, heavy duty trucks, electronic computers, and construction equipment. 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.

larger market share) due to competitors' technological advances (Aghion and Howitt, 1992; Antón et al., 2023; Becker and Ivashina, 2023; Bloom et al., 2013). Consequently, higher product market rivalry implies higher asset overhang.

To make the two measures comparable, we standardize each measure to have a mean equal to zero and a standard deviation equal to one, and ensure that negative values correspond to sectors with low asset overhang and positive values to sectors with high asset overhang.[11]

3.4. Data sources

For our analysis, we construct a unique firm-year level dataset by combining syndicated loan data, firm financial statement data, and firm patenting data. Below we provide details on each of the individual datasets and how they are combined.

First, we obtain loan data on U.S. syndicated loans from LPC DealScan. This data, which is commonly used to study how bank lending policies affect the real economy (Ivashina and Scharfstein, 2010; Saidi and Streitz, 2021), contains detailed information on loan terms (including the loan amount, loan pricing, loan maturity, and covenants), the banks involved in the loan, and the firm that receives the loan. Note that, although a loan syndicate is characterized by multiple lender types (namely lead arrangers and participant lenders), we follow Giometti et al. (2022) and Chakraborty et al. (2018) and attribute the entire loan amount of the syndicate to the lead arranger as the lead arranger is typically the lender in charge of screening and monitoring the borrower (e.g., Ivashina, 2009; Sufi, 2007).[12] In our main analysis we identify the lead arrangers based on the procedure outlined in Chakraborty et al. (2018), but we provide robustness tests based on the procedure of Ivashina (2009).[13]

We also apply the following filters. First, we drop loans that are granted to utilities

[11]This essentially means that we transform the asset redeployability measure to an asset irredeployability measure.

[12]In robustness, we show that our results hold if we use lead arrangers' actual loan share to compute bank specialization, and if we exclude term loans B (which banks usually sell in the secondary market after the syndication, see Irani et al., 2021).

[13]The procedure from Chakraborty et al. (2018) identifies lead lenders based on the following ranking hierarchy: 1) a lender is denoted as "Admin Agent," 2) a lender is denoted as "Lead bank," 3) lender is denoted as "Lead arranger," 4) a lender is denoted as "Mandated lead arranger," 5) a lender is denoted as "Mandated arranger," 6) a lender is denoted as either "Arranger" or "Agent" and has a "yes" for the lead arranger credit, 7) a lender is denoted as either "Arranger" or "Agent" and has a "no" for the lead arranger credit, 8) a lender has a "yes" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), 9) a lender has a "no" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary investor" are also excluded), and 10) a lender is denoted as a "Participant" or "Secondary investor." For a given loan package, the lender with the highest title (following the ranking hierarchy) is considered as the lead agent.

(public services) and financial firms. Second, using the linking table provided by Chakraborty et al. (2018), we consider the bank holding company as the ultimate provider of credit (as in Giannetti and Saidi, 2019; Giometti et al., 2022). Third, we drop loans with missing industry SIC codes. Fourth, we restrict our sample to loans originated after 1995 since the coverage of syndicated lending activity and loan contract terms in LPC DealScan is limited before that period (Chava and Roberts, 2008). Based on this, we aggregate the data at the bank-sector-year level to compute banks' sectoral specialization as defined in Section 3.1.

Second, we obtain annual information on firms' financial statements from Compustat. Particularly, we retrieve information on firms' balance sheet (including total assets and total debt), firms' profit and loss statements (including R&D expenses), and general firm information (including firms' industry classification and state of incorporation).

Third, we obtain patent data from PATSTAT, the largest available international patent database with comprehensive information on patent records, application dates, citations, and technology classes, among others. Using the data from PATSTAT we construct the patent output measures described in Section 3.2.

We merge the datasets 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 et al., 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 most firms borrow from one (lead arranger) bank, this aggregation affects only a limited set of firms.[14]

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

Table O1 in the Online Appendix for instance shows that, in a given year, more than 70% of the firms in our sample borrow from only one bank. Second, we match this data with the innovation measures computed from PATSTAT using the linking table from Arora et al. (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.

Our final dataset consists of 5,504 non-financial firms that operate in 58 (2-digit SIC) sectors spanning from 1996 until 2013.[15] These firms borrow from 131 unique banks active in the syndicated loan market. Table A1 in Appendix provides a definition of the variables used in our analysis.

3.5. Summary statistics

Panel A of Table 1 reports the distribution of the number of patents filed by the firms in our data sample between 1996 and 2013. The distribution of patents is clearly left skewed, with the 75$^{\text{th}}$ percentile of the distribution at zero. More precisely, firm-year observations with zero patents represent roughly 80% of the sample, firm-year observations with 1 or 2 patents about 5%, firm-year observations with 3–10 patents about 5%, and firm-year observations with 11–100 patents about 8%. The remaining 2% of the sample comprises firm-year observations with more than 100 patents. Panel B of Table 1 reports the distribution of (average) citations per patent in the sample. This distribution is also left skewed. We observe that only 6% of firm-year observations has more than 10 citations per patent. This suggests that most of the citations in the sample are received by a small number of highly cited (highly valuable) patents. These trends are consistent with those reported in Hall et al. (2001).

Table 2 provides descriptive statistics for firms that were granted at least one patent over the sample period and firms that were not granted any patents over the sample period (the

[15]The sample ends in 2013 due to the availability of the linking table provided by Arora et al. (2021). Our sample is also restricted due to the fact that we need to compute the number of citations received during the first five or seven years after a patent was granted (while it takes one to three years for patent applications to be denied or granted).

median number of patents per firm in the sample is zero). As indicated by the mean values reported in the table, firms with patents are larger (total assets of $940 billion compared to $620 billion), have higher R&D expenditures (5% of total assets compared to 1% of total assets), have a higher market-to-book ratio (0.93 compared to 0.64), have higher cash holdings (10% of total assets compared to 6% of total assets), and belong to slightly more concentrated industries (HHI of 0.21 compared to 0.18) than firms without patents. These statistics are in line with the ones reported by Atanassov (2013, 2016), among others. Further, we observe that firms with patents over the sample period have longer lending relationships (4.5 years compared to 4 years) and borrow from slightly less specialized banks (sectoral specialization of 5% compared to 6%). The last column of Table 2 shows that the difference in means between the two groups of firms is statistically significant for most statistics. Table O3 in the Online Appendix presents the pairwise correlations between the key independent variables, and indicates that there is little evidence of collinearity.

Figure 1 plots the distribution of banks' sectoral specialization. This figure shows that, while the loans to a particular sector usually represent less than 5% of a bank's (syndicate) loan portfolio, there are instances in which a particular sector represents more than 40% of a bank's loan portfolio. Thus, banks seem to specialize by concentrating their lending disproportionately in a few sectors. Figures O1 and O2 in the Online Appendix provide further evidence in line with this idea. Figure O1 shows the box-and-whisker plots of the distribution of bank specialization for each sector. For illustrative purposes, the bank specialization values in this figure are normalized (i.e., we normalized bank portfolio shares towards each sector s by the average share of lending in that sector). This figure shows that almost every sector has at least one or more right-tail outliers (i.e., every sector has one or more specialized lenders), indicating that bank specialization is common across sectors. Figure O2 presents distributional information on within-sector dispersion of bank specialization. This figure is constructed by computing a coefficient of dispersion, defined as the ratio of the difference and the sum of the 90$^{\text{th}}$ and 50$^{\text{th}}$ percentile of bank specialization, for each sector and each year. The larger this coefficient, the larger the within-sector differences in bank specialization. Thus, looking at the distribution of the coefficient of dispersion, Figure O2 indicates that there is large dispersion in bank specialization. In sum, bank specialization is an important feature of banks' lending policies and business model (also see Blickle et al., 2023).

Figure 2 plots a heat map of the degree of asset overhang across sectors using our two measures of asset overhang. This graph is constructed by computing, for each sector, the average (standardized) value of asset overhang over the sample period. The brighter (yellow) colors correspond to values with a higher degree of asset overhang, while the darker (purple) colors correspond to values with a lower degree of asset overhang. The final heat map appears reasonable. For example, the Textile Mill Products sector (SIC code 22) and Railroad Transportation sector (SIC code 40) are considered to have high asset overhang due to the low redeployability of the assets used in these sectors (such as cotton yarn mills and locomotives, respectively). Further, the Electrical Equipment sector (SIC code 36) is considered to be a sector with high product market rivalry, which is in line with anecdotal evidence on the product market rivalry observed among semiconductor manufacturing companies, for instance.[16] The correlation between the two measures is approximately 0.40, suggesting that the two measures capture different dimensions of the asset overhang problem.

4. Methodology

Our research objective is to examine how bank specialization affects corporate innovation or, in other words, how the sectoral specialization of a firm's lender affects the firm's innovation output. We start by testing Hypothesis 1, as described in Section 2, using the following regression model:

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

where f, b, s, and t refer to firm, bank, sector, and time, respectively. The outcome variable $y_{f,b,s,t}$ represents different firm innovation outcomes, such as patent quantity and quality.[17] $Bank\ specialization_{b,s,t-1}$ 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

[16] For instance, 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.

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

firm's lenders. $C_{f,b,s,t-1}$ is a vector of lagged control variables. $\lambda_{s,t}$ and $\lambda_{l,t}$ are sector-by-time and state-by-time fixed effects, respectively. 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.

Then, to test Hypothesis 2, as described in Section 2, 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:

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

where $Asset\ overhang_{s,t-1}$ corresponds to either of the two measures of asset overhang defined in Section 3.3. As mentioned before, the measures of asset overhang are standardized (meaning that each measure has a mean equal to zero and 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.

Following prior literature, 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 et al., 2011). In particular, we control for firm size, age, asset tangibility, capital expenditures, R&D expenditures, profitability, leverage, equity, growth opportunities, access to public debt markets, and product market competition. Firm size is proxied by the natural logarithm of total assets. Firm age is measured as the number of years since Initial Public Offering (IPO). Asset tangibility is measured as net property, plant, and equipment scaled by total assets. Capital expenditure is measured as capital expenditures scaled by total assets. R&D expenditures is measured as R&D expenditures scaled by total assets. Profitability is measured by return on assets. Leverage is proxied by total debt scaled by total assets. Equity is proxied by total equity scaled by total assets. Growth opportunity is proxied by Tobin's Q, which is computed as the market-to-book ratio. Public debt rating is a dummy variable equal to one if a firm has a public debt rating and zero otherwise, and proxies firms' access to public debt financing (as in Atanassov, 2016). Product market competition is measured by the Herfindahl–Hirschman index based on annual sales using 3-digit SIC codes. To account for potential non-linear effects of product market competition, we also control for the squared term of product market competition (Aghion et al., 2005).

Further, we also control for a set of bank and bank-firm characteristics that could influence firms' innovation output. First, using Italian data, Herrera and Minetti (2007) show that longer lending relationships have a positive effect on firms' product and process innovation. We therefore control for the length of the firm-bank relationship, measured as the number of years during which a bank-firm pair has maintained a lending relationship. Second, since Deng et al. (2021) show that banks' geographic diversification spurs corporate innovation, we include a control variable that captures banks' geographic diversification (computed based on the Herfindahl-Hirschman index).[18] Third, previous research has highlighted the relevance of bilateral versus multilateral financing in (the information disclosure cost of) firms' innovation activities (Bhattacharya and Ritter, 1983; Bhattacharya and Chiesa, 1995). To account for this, we control for the number of lending relationships that a firm maintains, measured as the number of lead arrangers that a firm borrows from in a given year. Fourth, Saidi and Streitz (2021) find that higher bank concentration reduces product market competition between non-financial firms. Given that product market competition can influence firms' innovation incentives (Aghion et al., 2005), we also control for the bank concentration within each 3-digit SIC sector. Finally, we control for a bank's market share in a specific sector to account for the bank's pricing power and the bank's willingness to internalize losses from sector-specific shocks (Giannetti and Saidi, 2019).[19]

In addition to a large set of control variables, our regression model also includes sector-by-

[18]Specifically, this Herfindahl-Hirschman index is computed as the sum of the squared ratios of credit granted by a bank to firms in each state to the sum of total credit granted by a bank in all states.

[19]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 O3 in the Online Appendix shows that the correlation between these two variables is relatively modest ($\rho = -0.13$).

time and state-by-time fixed effects, represented by $\lambda_{s,t}$ and $\lambda_{l,t}$, respectively. The former control for sector-specific time-varying unobserved heterogeneity, such as differences in financing or patenting behavior across sectors. The latter control for state-specific time-varying unobserved heterogeneity, such as local economic policies and business cycles.

To estimate Equations (2) and (3), we employ a fixed effects Poisson model. The reason for doing so is because our main outcome variables (i.e., the quantity and quality of firms' patents) are count-based variables. Research has shown that estimating a linear regression model with a logarithmic transformation of count-based variables can produce biased estimates, while a fixed effects Poisson model produces consistent and reasonably efficient estimates under more general conditions (see Cohn et al., 2022; Wooldridge, 1999).[20] We employ OLS regression when we estimate the effect of bank specialization on the originality and generality of firms' patents (which are not count-based variables). In robustness tests, discussed below, we show that our results hold using alternative specifications, estimation methods, and fixed effects structures, among others.

5. Results

The results section is structured as follows. We first examine the effect of bank specialization on the different dimensions of firms' innovation output. Next, we explore the underlying mechanism through which bank specialization could affect corporate innovation. Finally, we present a number of extensions and robustness tests.

5.1. Baseline results

We start by testing Hypothesis 1, which posits that bank specialization has a positive effect on firms' innovation output, using the regression model outlined in Equation (2). The results from estimating this equation are presented in Table 3. In this table, the outcome variable is the number of patents in columns (1) and (2) and the average number of patent citations in columns (3) and (4). We report regression results with two different sets of fixed effects

[20] 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 et al., 2022; Guimaraes, 2008).

to assess the stability of the coefficient estimates. To assess the goodness of fit of the fixed effects Poisson regressions, we report the Pseudo R-squared.

We first focus on the coefficient estimates of our control variables in Table 3, which are broadly in line with previous findings in the literature. For instance, we find that firms' innovation output is positively related to their size, fixed assets, cash holdings, ROA, R&D expenses, Tobin's Q, and access to public debt markets, and negatively related to their leverage, which accords with results reported by Amore et al. (2013) and Atanassov (2013, 2016), among others.

Turning to the coefficient estimates of *Bank specialization*, our independent variable of interest, the results in Table 3 consistently show that there is a statistically insignificant effect of bank specialization on the quantity and quality of firms' patents. The estimated effects are very stable across the different fixed effects structures, and the corresponding p-values are between 0.60 and 0.98, which is far from conventional significance levels. Thus, inconsistent with Hypothesis 1, these results suggest that, on average, bank specialization does not have a positive effect on firms' innovation output.

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 exploit heterogeneity in asset overhang across sectors, i.e., the risk that a new technology would adversely affect the value of a bank's legacy loan portfolio (Degryse et al., 2023). The two measures of asset overhang that we use are explained in Section 3.3, each of which relates to at least one of the two key mechanisms through which new technologies can adversely affect the value of (the existing technologies underlying) a bank's legacy loan portfolio, namely (1) a reduction in firm value due to a devaluation of the firm's pledged collateral, or (2) a reduction in firm value due to a decrease in firm performance (Aghion and Howitt, 1992; Bloom et al., 2013; Schumpeter, 1943; Utterback, 1994).

Using our two measures of asset overhang, we test Hypothesis 2, which posits that the effect of bank specialization on corporate innovation depends on the asset overhang of the sector in which a firm operates. Particularly, we estimate Equation (3) which includes an interaction term between the sectoral specialization of a firm's lender and the asset overhang of the sector in which the firm operates. The results are presented in Table 4. In this table, columns (1) and (2) report the results for the number of patents while columns (3) and (4) report the results for the average number of patent citations. The measure of asset overhang used for the corresponding results is indicated at the bottom of the table. All regressions include sector-by-time and state-by-time fixed effects.[21] For brevity, this table does not report the coefficient estimates of the control variables.

Focusing on the results presented in columns (1) and (2) of Table 4, which are based on firms' number of patents as outcome variable, we find a significantly negative coefficient estimate for the interaction term between *Bank specialization* and *Asset overhang*. Recall that the values of *Asset overhang* are smaller than zero for sectors with low asset overhang and larger than zero for sectors with high asset overhang. Thus, our coefficient estimates indicate that the effect of bank specialization on the number of patents 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 also economically significant. Column (1) for instance indicates that, in sectors with low (high) asset overhang, a one standard deviation increase in bank specialization in associated with a 15% increase (decrease) in the number of patents.

Columns (3) and (4) of Table 4 present the estimated effects on the quality or economic value of firms' patents (measured as the average number of citations per patent). Consistent with our results on patent quantity, the effect of bank specialization on patent quality is positive in sectors with low asset overhang, and negative in sectors with high asset overhang. The economic magnitudes of these effects are comparable to those in columns (1) and (2) as well. Column (3) for instance indicates that, in sectors with low (high) asset overhang, a one standard deviation increase in bank specialization in associated with a 12% increase (decrease) in the number of patent citations. In sum, consistent with Hypothesis 2, the results in Table 4 indicate that borrowing from a specialized bank improves the innovation output

[21] Note that the variables of asset overhang are absorbed by the sector-by-time fixed effects and, hence, not reported in the tables discussed below. Unreported regressions with sector and time fixed effects show an insignificant coefficient for the asset redeployability measure and a significantly positive coefficient for the product market rivalry measure.

of firms operating in sectors with low asset overhang, but impedes the innovation output of firms operating in sectors with high asset overhang. In robustness tests, discussed below, we show that this result holds when we exploit exogenous variation in bank specialization arising from bank mergers (e.g., as in Giannetti and Saidi, 2019; Iyer et al., 2022).

Next, we also study the impact of bank specialization on the novelty (or nature) of firms' innovation activities, which we measure based on the originality and generality of firms' patents (as explained in Section 3.2). In particular, we re-estimate Equations (2) and (3) with patent originality and generality as outcome variables. Since patent originality and generality are continuous variables ranging between zero and one, we estimate these regressions using OLS.

The results from re-estimating Equation (2) for patent originality and generality are presented in Table 5 and show that, on average, bank specialization does not affect the originality or the generality of firms' patents. This is in line with our results from Table 3 and could be due to the fact that the effect depends on the underlying asset overhang. Therefore, we turn to Table 6, which present the results from re-estimating Equation (3) for patent originality in columns (1)–(2) and patent generality in columns (3)–(4). Recall that higher values of originality or generality mean that a patent is drawing on or being drawn upon by a more diverse array of technologies, suggesting that the patent has broader (or more radical) applications (Hall et al., 2001; Lerner et al., 2011). In line with the estimated effects on patent quantity and quality, Table 6 suggests that bank specialization has a positive effect on patent novelty in sectors with low asset overhang, and a negative effect on patent novelty in sectors with high asset overhang. These estimated effects are economically significant. Column (1) for example indicates that, in sectors with low (high) asset overhang, a one standard deviation increase in bank specialization in associated with a 5% increase (decrease) in the originality of firms' patents. Thus, these results imply that bank specialization does not only matter for the quantity and quality of firms' innovations, but also for the radicalness (or nature) of firms' innovations, which is an important insight given that radical innovation is the most important driver of long-term economic growth (Acemoglu, 2008).

In sum, in line with our second hypothesis, we find that the effect of bank specialization on corporate innovation depends on the asset overhang of the sector in which a firm operates. Our results show that bank specialization has a positive effect on the innovation output of firms operating in sectors with low asset overhang and a negative effect on the innovation output of firms operating in sectors with high asset overhang, a novel pattern that has not been predicted or documented by previous papers. Thus, our results uncover bank specialization—a defining feature of banks' business model—as an important channel through which the banking sector could enhance or distort corporate innovation and economic growth.

5.1.1. Innovation survey results

The impact of bank lending policies on real firm outcomes, including firms' innovation activities, has been extensively analyzed for the U.S (e.g., Hombert and Matray, 2017; Nanda and Nicholas, 2014; Saidi and Žaldokas, 2021). Yet, two potential concerns could be that our U.S. data sample only covers certain types of innovation output (i.e., patented innovations) and certain types of firms (i.e., large, typically listed firms). To mitigate these concerns, we construct a second dataset based on Belgian credit register data combined with self-reported information on firms' innovation output from the Belgian input to the Community Innovation Survey (CIS) administered by the European Commission.

The CIS is the main instrument in Europe that collects data on firms' innovation activities. The survey is carried out on a bi-annual basis by national statistical offices throughout the European Union according to the EU-wide definitions of the Oslo Manual (OECD, 2005), and is designed to collect information on firms' product and process innovations, innovation strategies, and factors that facilitate or hinder innovation. The CIS is used for the European Innovation Scoreboard as well as for academic research on innovation. For instance, in the literature on banking and innovation, the CIS has recently been used by Schmidt et al. (2023), and comparable innovation survey data has been used by Nanda and Nicholas (2014) (for the U.S.), Benfratello et al. (2008) (for Italy), and Bircan and De Haas (2020) (for Russia).

The CIS complements our U.S. data sample in two important ways. First, the CIS asks firms about all types of innovation activities, irrespective of whether those innovations are (ultimately) patented. This is important as not all firms use the patent system, meaning that the CIS may give a more accurate measure of firms' innovation output and mitigate potential concerns about the role of the patent-secrecy trade-off in bank lending (Saidi and Žaldokas, 2021). Second, the CIS covers all types of firms, including many small (private) firms that are heavily dependent on bank financing.[22] In contrast to the large (public) firms used in our baseline analysis, the firms included in the CIS cannot easily access public debt markets and face high switching costs, which mitigates potential concerns about the influence of alternative financing sources.

We have access to the Belgian version of the CIS data for the six surveys carried out between 2008 and 2020. Following prior research, we construct two indicator variables that equal one if a firm introduces a product or process innovation, respectively. The former concerns new or significantly improved goods or services, while the latter concerns new or significantly improved methods of production or logistics, among others. We also create a third indicator variable that equals one if a firm introduces a world-first innovation (i.e., an innovation that has never been introduced anywhere else in the world). Thus, in line with our baseline analysis, we capture both the quantity and quality (or novelty) of firms' innovation.

We then link the Belgian version of the CIS data to the Belgian credit register and firm balance sheet data administered by the National Bank of Belgium. The credit register data allow us to identify each firm's bank lending relationships and the sectoral specialization of those banks.[23] Further, the balance sheet data allow us to obtain a series of firm controls such as firm size, age, leverage, and profitability (similar to the ones used in our baseline analysis) as well as to compute a measure of asset overhang for firms operating in Belgium. Specifically, as data on asset redeployability and product market rivalry are not available for Belgium, we construct a sector-year level measure of capital intensity, computed as the sector-year level average of firms' fixed assets to total assets. The idea is that firms operating in sectors with high capital intensity tend to invest in projects that require large upfront costs, often for physical assets that are specific to their line of business (Gulen and Ion, 2016). This implies

[22]The base population of the CIS comprises all firms with ten or more employees operating in sectors with the following two-digit NACE codes: 05-39, 46, 49-53, 58-66, and 71-73. Based on this population, stratified random sampling based on firms' economic activity, size, and region is used to ensure the surveyed sample is representative for the base population.

[23]The variation in sectoral specialization of banks active in the Belgian banking sector is broadly similar to the variation observed for banks active in the syndicated loan market, see for instance De Jonghe et al. (2024).

that, for a firm operating in a sector with high capital intensity, a new technology that would render existing products or infrastructure obsolete could lead to a large devaluation of the firm's assets (Baldwin, 1982; Choi, 1994; Pindyck, 1986).[24]

Using these data and the regression models specified in Equations (2) and (3), we study the effect of lenders' sectoral specialization on firms' survey-based innovation output, and how this effect depends on the asset overhang of the sector in which a firm operates.[25] The results are reported in Tables 7 and 8. Across the different columns, we report the results for product innovations, process innovations, and world-first innovations. Note that the third column has less observations due to the fact that the question on world-first innovations is not available for the 2018 survey wave.

In line with our baseline results, the results in Table 7 show that, on average, bank specialization does not affect firms' innovation output. Nevertheless, columns (1) and (3) of Table 8 show significantly negative coefficient estimates for the interaction term between bank specialization and asset overhang. This is consistent with our earlier results and indicates that, in sectors with low (high) asset overhang, lenders' sectoral specialization has a positive (negative) effect on the probability that firms introduce product innovations and world-first innovations. In terms of economic significance, 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 insignificant coefficient estimate in column (2) is not surprising, as process innovations have smaller spillovers than product innovations (e.g., Aghion et al., 2022).

Overall, our results obtained from the Belgian innovation survey data combined with credit register data are in line with our baseline results. 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.

[24]We recognize that capital intensity is a rough proxy as it does not explicitly take into account asset specificity or mobility.
[25]Descriptive statistics on our Belgian data sample can be found in Table O4 in the Online Appendix.

5.2. Mechanism

We have shown that bank specialization has heterogeneous effects on corporate innovation, and that these heterogeneous effects stem from differences in asset overhang across sectors. A question that remains to be answered, however, 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 (Amiti and Weinstein, 2018; Chava and Roberts, 2008).

To this end, we first test how a bank's sectoral specialization affects a firm's financing conditions, following the approach from Blickle et al. (2023) and Giometti et al. (2022). Then, we extend their approach and analyze whether this effect also depends on the innovativeness and the asset overhang of the sector in which a firm operates. To implement this approach, we use the syndicated loan data, which contains detailed information on loan conditions, and aggregate it at the bank-firm-year level to estimate the following OLS regression:

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

where the outcome variable $y_{f,s,b,t}$ corresponds to the loan conditions offered by bank b to firm f operating in sector s for loans originated 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. Following Chava et al. (2013), innovative sectors are defined as sectors with above-average patents in year $t-1$. $High\ asset\ overhang_{s,t-1}$ 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 two measures of asset overhang as defined in Section 3.3). $C_{f,s,t-1}$ corresponds to the vector of control variables used in Equation (2), and $\lambda_{b,t}$, $\lambda_{s,t}$, and λ_f, correspond to bank-by-time, sector-by-time, and firm fixed effects, respectively.[26] The error term is represented by $\epsilon_{b,s,t}$ and clustered at the firm-bank level. The coefficients of interest in Equation (4) are β_1 and β_4. The former captures the average effect of bank specialization on firms' borrowing terms. The latter 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.

In estimating Equation (4), we focus on three key loan conditions. First, we study loan rates (measured as the all-in-drawn spread—AISD) to study whether specialized banks charge a risk premium to firms operating in innovative sectors with higher asset overhang. The idea is that, if banks are aware of the potential negative spillovers of technology-induced shocks, they would charge higher loan rates to compensate for that risk.

Second, we study loan maturities and covenants—two key dimensions through which banks can influence firms' investments in innovation activities. Short loan maturities create liquidity or refinancing risk, which refers to the risk that, when refinancing, changes in market conditions or capital market imperfections could force firms to refinance at less favorable conditions (Froot et al., 1993) or that, when refinancing, lenders could underestimate the continuation value of the firm and not allow refinancing to take place (Brunnermeier and Yogo, 2009; Diamond, 1991, 1993). Given that the propensity of firms to undertake innovation depends on their ability to satisfy current R&D expenditures and their ability to borrow in the future to meet potential adjustment costs, refinancing risk (due to short loan maturities) can directly impede firms propensity to innovate (Aghion et al., 2010; Hall and Lerner, 2010).

Restrictive debt covenants, on the other hand, can constrain firms' financial and operational flexibility (Chava and Roberts, 2008; Nini et al., 2009).[27] Broadly, violating a loan covenant shifts control rights to lenders, which gives them the right to recall the loan, renegotiate the loan, or impose penalties. Consequently, lenders may use the threat of terminating the loan or accelerating the loan to influence borrowers' financial and investment decisions. Lenders

[26]The bank-by-time fixed effects control for bank-specific time-varying unobserved heterogeneity (such as differences in credit supply or regulatory requirements), the sector-by-time fixed effects control for sector-specific time-varying unobserved heterogeneity (such as differences in loan demand or patenting behavior across sectors), and the firm fixed effects control for firm-specific time-invariant heterogeneity.

[27]Covenants increase creditor control rights and can have substantial effects on borrowers' financial and investment decisions (Chava and Roberts, 2008; Nini et al., 2009; Roberts and Sufi, 2009). Using syndicated loan data, Nini et al. (2009) for instance find that 32% of loan contracts contain an explicit restriction on firms' capital expenditures, which reduces firms' investments.

could, for instance, force borrowers to divest assets, switch to lower-risk investments, or switch to short-term (cash-flow-generating) investments. Given the long-term, risky nature of innovation activities, innovative firms may be particularly vulnerable to the enhanced bargaining power of lenders (Atanassov, 2016; Deng et al., 2021).[28]

Table 9 present the results from estimating Equation (4) with each of the three loan outcomes. Panels A to C present the regression results with loan rates, covenant strictness, and maturity as outcome variables, respectively, where covenant strictness is measured based on the covenant violation probability computed by Demerjian and Owens (2016).[29] In column (1), we estimate the average effect of bank specialization on firms' borrowing terms, without any of the interaction terms outlined in Equation (4). Then, in columns (2) and (3), we saturate the model with the interaction terms outlined in Equation (4) using both measures of asset overhang, as indicated at the bottom of the table.

Focusing on Panel A of Table 9, column (1) shows that, on average, bank specialization does not affect firms' loan rates. However, columns (2) and (3) indicate that specialized banks charge significantly higher loan rates (compared to non-specialized banks) to firms operating in innovative sectors with high asset overhang. This is consistent with the idea that specialized banks are aware of the potential negative spillovers of technology-induced shocks and require compensation to take on this risk.

Turning to column (1) of Panels B and C, we find that, on average, firms borrowing from more specialized banks obtain loans with less restrictive covenants and longer loan maturities. For one, column (1) of Panels B and C indicate that each one standard deviation in the sectoral specialization of a firm's lender is associated with a 5% decrease in covenant strictness and a 1% increase in loan maturity, respectively. These results accord with evidence from

[28]Although it is common for loan contracts to contain covenants that restrict firms' capital expenditures, loan contracts generally do not contain covenants that explicitly restrict firms' innovation activities. Nevertheless, covenants can indirectly restrict firms' innovation activities. For instance, the majority of loan covenants are tied to firm' net worth or firms' ratio of debt to earnings before interest, tax, depreciation, and amortization (EBITDA) (Chava and Roberts, 2008). Given that innovation inputs (such as R&D expenditures) are expensed instantly, innovation inputs reduce firms' EBITDA and net worth. Thus, loan covenants can force firms to curtail their innovation activities to meet loan covenant thresholds (Deng et al., 2021). Put differently, loan covenants could force borrowing firms to switch from innovative, long-term investments to less risky, short-term projects that generate more stable cash flows and allow to meet loan covenant thresholds.

[29]In Table O5 in the Online Appendix, we also show regressions results with loan amounts as outcome variable. Consistent with previous papers, we find that bank specialization is associated with larger loan amounts. We do not find statistically significant evidence that this differs for firms operating in innovative sectors with high asset overhang. We do not analyze the effect of bank specialization on collateral requirements (and how this effect varies across sectors) as the data on collateral in LPC DealScan is very scarce.

Blickle et al. (2023) and Giometti et al. (2022) that bank specialization eases firms' financial constraints, which could in principle improve firms' innovation output.

Nevertheless, columns (2) and (3) of Panels B and C indicate that firms operating in innovative sectors with high asset overhang obtain less favorable (instead of more favorable) loan conditions from specialized banks. This can be observed from the coefficient estimates of β_4, which are significantly negative across the different panels. For one, the coefficient estimates of β_1 and β_4 in column (3) of Panel B equal -0.33 and 0.97, respectively, and are both statistically significant. These estimates imply that, on average, a one standard deviation increase in bank specialization leads to a 6% decrease in firms' debt covenant strictness but, for a firm operating in an innovative sector with high asset overhang, a one standard deviation increase in bank specialization is associated with a 10% increase in debt covenant strictness. As explained earlier, tight debt contracts constrain firms' operational and financial flexibility (Chava and Roberts, 2008; Nini et al., 2009), which could reduce firms' propensity to undertake risky, innovative projects.

Taken together, our results indicate that the heterogeneous effects of bank specialization on corporate innovation arise through banks' traditional role as financier of firms' investments (as in Amore et al., 2013; Deng et al., 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.

5.3. Robustness

5.3.1. Endogeneity

Our baseline models control for a broad range of firm and bank characteristics as well as fixed effects, yet a potential concern remains that the endogeneity of lenders' sectoral specialization may bias our results. We attempt to address this concern using two approaches.

First, following prior research, we exploit mergers between banks that are 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).[30] 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 the 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 $\Delta Bank\ specialization^{merger}_{b,s}$ 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 et al., 2024), which we use to run the following regression model:

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

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

The results are reported in Tables A2 and A3 in Appendix and provide evidence that our baseline findings hold using this particular sample and test design. Table A2 first confirms that, on average, merger-induced changes in bank specialization do not have a statistically significant effect on firms' innovation output. Then, exploiting heterogeneity in asset overhang, Table A3 shows 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 0.11). 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

[30]We follow previous papers and restrict our focus to mergers between two BHCs that each have at least \$1 billion in assets preceding the merger.

(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 potential endogeneity concerns, we test for endogenous matching between banks and firms. For instance, it could be that, in sector with high (low) asset overhang, firms with less (more) innovation output are more likely to borrow from more (less) specialized banks. Although this seems unlikely, we use a similar approach as Foà et al. (2019) to test whether this could be the case. In particular, we test the relationship between a firm's innovation output and a bank's specialization the first time that the firm and the bank entered into a loan agreement, and how this relationship depends on the asset overhang of the sector in which the firm operates. Formally, we aggregate the syndicated loan data at the firm-bank-year level and estimate the following regression 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 refer to firm, sector, bank, and time, respectively. The outcome variable is the number of patents or patent citations from firm f over the three years prior to entering a loan agreement with bank b. The control variables are similar to the ones used in our baseline regressions, but we add a series of additional bank controls to test which other bank characteristics could affect 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 (i.e., the first time that a firm and a bank "matched").

The results are presented in Table A4 in Appendix. Overall, we do not find evidence of endogenous matching as the coefficient estimate of δ is statistically insignificant across all columns. This implies that our results are not due to the endogenous matching of more (less) innovative firms and more (less) specialized banks in sectors with low (high) asset overhang.

5.3.2. Alternative channels

We study two alternative channels that could give rise to our results. First, we study the potential role of zombie lending as an alternative channel. Recent research by De Jonghe et al.

(2024) shows that bank specialization reduces zombie lending, while Schmidt et al. (2023) show that zombie lending impedes innovation. This suggest that our results may partly be driven by the fact that bank specialization reduces zombie lending which, in turn, increases firms' innovation output.

To show that our results are not driven by this channel, we re-estimate our baseline results while controlling for lenders' sectoral zombie lending. To define zombie firms, we use the definition from Banerjee and Hofmann (2022) who consider a firm to be a zombie if the firm's interest rate coverage ratio[31] is below one and the firm's Tobin's Q is below the median within the firm's sector, and these two criteria have been satisfied for two consecutive years. Either of these two criteria has to be violated for two consecutive years before a firm leaves the zombie classification. Based on this, we create a measure that captures the proportion of a bank's lending to zombie firms within a given sector and year compared to the bank's total lending within that sector and year.[32] The results are presented in Panel A of Table A5 in Appendix. Consistent with Schmidt et al. (2023), we find that banks' zombie lending has a significantly negative effect on the number of patents filed (although we do not find a significant effect on firms' patent citations).[33] Nevertheless, controlling for banks' sectoral zombie lending does not change our baseline results as the interaction term between banks' sectoral specialization and asset overhang remains negative and statistically significant.[34]

Second, we study whether our results could be due to banks' technological conservatism, a potential mechanism proposed by Minetti (2011) in the context of relationship lending. In particular, Minetti (2011) argues that the information that banks collect over the course of a lending relationship may be specific to the mature technologies underlying that relationship.

[31]A firm's interest coverage ratio is defined as the ratio of earnings before interest and taxes over interest payments.

[32]Specifically, we compute a bank's sector-specific zombie lending as follows:

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

where $Credit_{b,f,t}$ is the credit granted by bank b to firm f operating in sector s at time t. $Zombie_{f,t}$ is an indicator variable equal to one if firm f is a zombie firm. F^s and S correspond to the total number of firms and sectors, respectively.

[33]Schmidt et al. (2023) only analyze the effect of banks' zombie lending on firms' patents (not on firms' patent citations). A potential reason why we do not find a significant effect for the latter estimates could be because zombie lending causes firms to re-focus their efforts on their most innovative projects and abandon pet projects, which could lead to a decline in the number of patents without a change in the average number of patent citations (Lerner et al., 2011).

[34]One may still be concerned that our results are driven by zombie firms if our measures of asset overhang are highly correlated with the proportion of zombie firms across sectors. In unreported results, we find that our baseline results also hold if we split our sample into sectors with a low and high proportion of zombie firms.

Put differently, the information that a lender collected about a mature technology (and the productive assets underlying those technologies) may not be easily transferable to a new technology, meaning that the lender's information could go to waste if a new technology comes in. Anticipating this, the lender may have an incentive to impede technological change in order to preserve the value of its proprietary information about the mature technologies.

To rule out this alternative channel, we re-estimate our baseline results including an interaction term between bank specialization and a dummy variable equal to one for firms operating in informationally complex sectors. The reasoning behind this test is that we would expect technological conservatism to be more relevant for firms operating in such sectors. To this end, we follow prior literature and use the product differentiation classification from Rauch (1999) to build a measure of informational complexity. Rauch (1999) distinguishes between three product categories: products that are traded on organized exchanges, product that are reference priced, and products that are not traded on organized exchanges nor reference priced. Similar to previous papers (e.g., Cao et al., 2023; Iyer et al., 2022), we use this classification to split our sample into "complex" sectors (i.e., sectors where products are not sold on an exchange nor reference priced) and "simple" sectors (i.e., the remaining sectors).[35] Then, we re-estimate equation (3) but we add an interaction term between bank specialization and the dummy variable for informationally complex sectors. The results are presented in Panel B of Table A5 in Appendix and show that the interaction term between bank specialization and asset overhang remains quantitatively similar to our baseline results, while the interaction term between bank specialization and our proxy of informational complexity is statistically insignificant. Put differently, the informational complexity of a sector does not seem to play a role, mitigating concerns that our results are due to the technological conservatism channel proposed by Minetti (2011).

Third, we study whether there are other interaction terms between asset overhang and (observable) bank characteristics—such as banks' market share or bank competition—that give rise to a similar effect as the interaction term between asset overhang and bank specialization.

[35] In our sample, approximately 30% of firms are classified as firms with heterogeneous products, a figure in line with Campello and Gao (2017) and Cao et al. (2023).

Our results, which are presented in Table A6 in Appendix, show that the interaction term between asset overhang and bank specialization is consistently negative and statistically significant, while this is not the case for any of the other interaction terms, confirming the relevance of the channel that we document.

Finally, one may be concerned that bank specialization is correlated with other, unobserved firm- or bank-specific characteristics. To address this concern, we show that our results hold if we saturate our regression model with more stringent fixed effects. Panel A of Table A7 in Appendix for instance shows that our results hold when we include firm fixed effects, which account for any firm-specific unobserved heterogeneity. Note that, by construction, including firm fixed effects restricts our sample to firms that patent at least once over the sample period, meaning that these estimates can also be interpreted as an intensive margin effect. Panel B of Table A7 in Appendix shows that our results also hold when we include bank-by-time fixed effects, which account for any type of bank-specific time-varying unobserved factors that could jointly influence banks' specialization and lending decisions.[36]

5.3.3. Alternative measures of bank specialization

We re-estimate our baseline results using alternative measures of bank specialization. First, in Panel A of Table O6 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 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. Despite these technical differences, the results presented in Panel A of Table O5 are similar to our baseline results.

Second, in Panel B of Table O6 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

[36]The results in Panel B of Table A7 in Appendix are estimated based on a sample of firms with one bank (lead arranger) relationship to avoid duplicate observations of firm innovation outcomes. Unreported analyses confirm that our results remain quantitatively similar if we use the entire sample and weigh observations based on banks' share in firms' outstanding credit.

and the sector-by-time fixed effects in these regressions are also based on 3-digit instead of 2-digit SIC codes. In line with our baseline results, we find that, in sectors with low (high) asset overhang, bank specialization positively (negatively) affects firms' innovation output.

5.3.4. Data sample and measurement

We conduct various robustness checks related to the composition of our data sample, measurement choices, and empirical regression model. First, Panel A of Table O7 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 et al. (2018). Second, Panel B of Table O7 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 omits potential concerns about measurement error.

Third, recent research has shown that banks usually sell term loans B in the secondary market after the syndication (see Irani et al., 2021). Although banks could still gain expertise from originating this type of loans, Panel A of Table O8 in the Online Appendix shows that excluding these loans from our sample does not affect our estimates. Fourth, 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 B of Table O8 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.

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. Descriptive statistics presented in Table O1 in the Online Appendix show that borrowing from multiple banks is not very common (i.e., more than 70% of observations corresponds to firms with a single lender), mitigating concerns that using a weighted measure of bank specialization could generate noise in our estimates. Nevertheless, to resolve any remaining concerns, Panel A of Table O9 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 et al., 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 O9 in the Online Appendix shows that our results hold if we exclude recession periods (as defined by the NBER Business Cycle Dating Committee).

5.3.5. Empirical model

Our results are robust to alternative estimation methods and specifications. Panels A and B of Table O10 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 O11 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:

$$\begin{aligned} y_{f,b,s,t} =& \delta_1 Bank\ specialization_{b,s,t-1}^{Low\ asset\ overhang} + \delta_2 Bank\ specialization_{b,s,t-1}^{Moderate\ asset\ overhang} \\ &+ \delta_3 Bank\ specialization_{b,s,t-1}^{High\ asset\ overhang} + \gamma C_{f,b,s,t-1} + \lambda_{s,t} + \lambda_{l,t} + \epsilon_{f,b,s,t} \end{aligned} \tag{8}$$

where δ_1, δ_2, and δ_3 capture the effect of bank specialization on corporate innovation in sectors with low, medium, and high asset overhang, respectively, which allows the effects to be asymmetric. The results from estimating Equation (8) are presented in Table O12 in the Online Appendix. This table shows that the economic magnitudes of the coefficient estimates of δ_1 are slightly larger than those of δ_3 (the p-value of the coefficient estimate of δ_3 in column (4) is 0.11). This indicates 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.

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 et al., 2023; He et al., 2023). 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 et al., 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 different but complementary institutional environments. Our first dataset combines U.S. syndicated loan data with patent data. Our second dataset combines micro-level innovation survey data with credit register data from a representative European country (Belgium). 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 et al., 2023). Using two 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 favorable loan conditions, except to firms operating in innovative sectors with high asset overhang. The latter receive less (instead of more) favorable loan conditions if they borrow from specialized banks. 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 product market rivalry and asset redeployability—impact banks' incentives to finance innovation, thereby contributing to our understanding on how financial and product markets interact.

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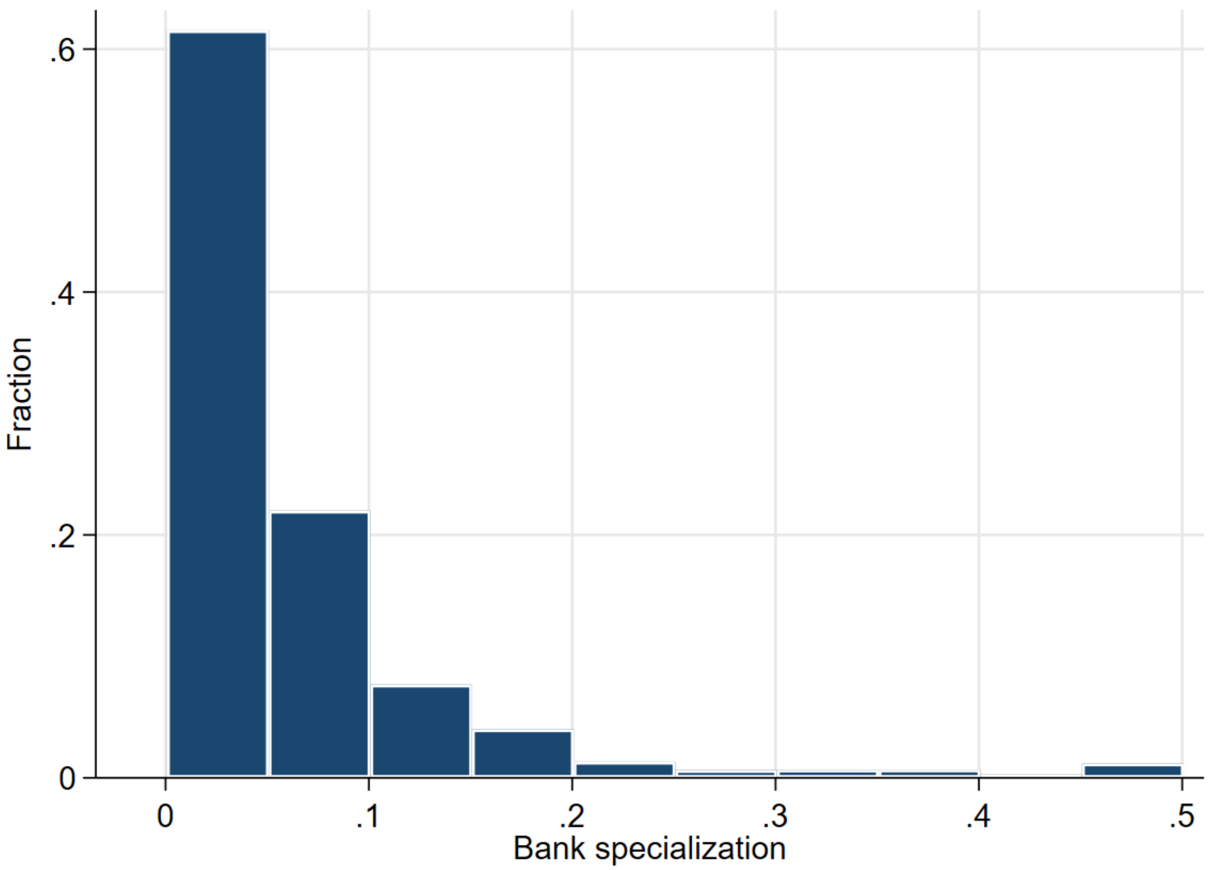
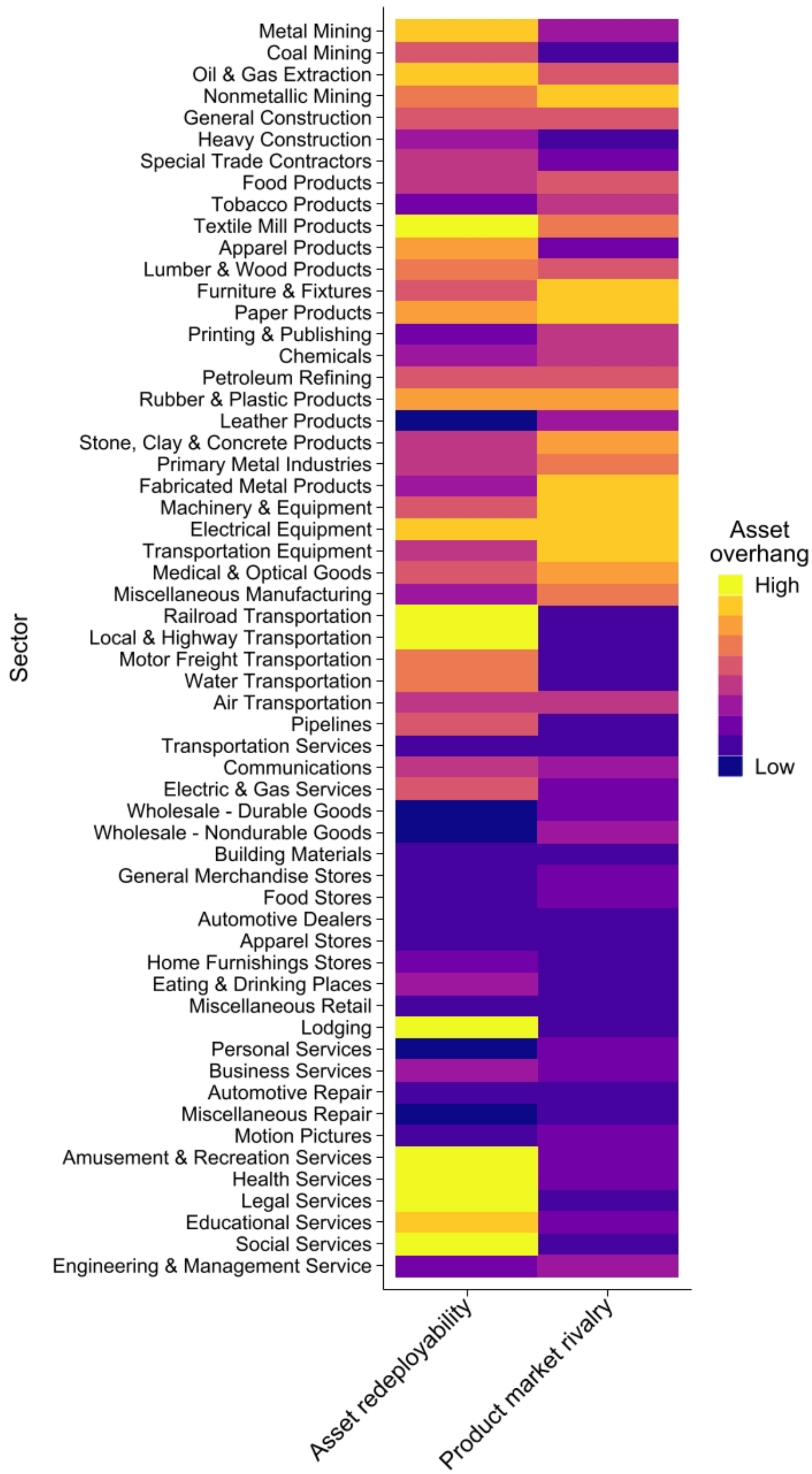
Figures

Figure 1: The distribution of banks' sectoral specialization



Note: This histogram presents the distribution of bank specialization. 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.

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



Note: This figure presents a heat map of the degree of asset overhang across sectors. For each sector, we compute the average of the standardized value of asset overhang, using each of our two measures of asset overhang described in Section 3.3. 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. The correlation between the two measures is approximately 0.40.

Tables

Table 1: Summary statistics: Patents and patent citations

	Median	75%	85%	90%	95%	99%	Max	Mean	SD	Observations
Panel A: Patents	0	0	3	9	36	107	159	5.3	19.2	35,023
Panel B: Citations	0	0	4.8	7.3	11.5	25.4	82.9	2.0	5.8	35,023

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 2: Summary statistics: Patenting versus non-patenting firms

	Patenting firms		Non-patenting firms		
	Mean	SD	Mean	SD	Difference
Patents	17.87	31.94	0.00	0.00	-17.87***
Patent citations	6.60	9.00	0.00	0.00	-6.60***
Patent originality	0.36	0.30	0.00	0.00	-0.36***
Patent generality	0.58	0.41	0.00	0.00	-0.58***
Size	6.85	1.88	6.43	1.84	-0.42***
Age	4.24	6.33	3.55	5.46	-0.69***
Debt/TA	0.25	0.20	0.34	0.26	0.09***
Equity/TA	0.44	0.22	0.37	0.23	-0.07***
Cash/TA	0.10	0.11	0.06	0.10	-0.04***
ROA	0.01	0.20	-0.00	0.20	-0.01***
Fixed assets/TA	0.50	0.32	0.60	0.41	0.11***
CAPEX/TA	0.05	0.04	0.06	0.06	0.02***
R&D expenses/TA	0.05	0.08	0.01	0.05	-0.04***
Tobin's Q	1.19	1.51	0.64	0.97	-0.55***
Public debt rating	0.93	0.26	0.65	0.48	-0.28***
HHI	0.21	0.15	0.18	0.14	-0.03***
Bank specialization	0.05	0.06	0.06	0.08	0.01***
Bank market share	0.17	0.15	0.14	0.14	-0.02***
Bank concentration	0.32	0.15	0.29	0.14	-0.03***
Bank geographic diversification	0.89	0.17	0.87	0.19	-0.02***
Number of lending relationships	1.38	0.73	1.37	0.71	-0.01
Lending relationship length	4.47	3.19	4.07	3.05	-0.40***
Observations	10,403		24,620		35,023

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 3: Bank specialization and corporate innovation: Patents and patent citations

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.01	-0.02	0.08	0.19
	(0.60)	(0.61)	(0.41)	(0.41)
Size$_{t-1}$	0.80***	0.81***	0.28***	0.30***
	(0.03)	(0.03)	(0.02)	(0.02)
Age$_{t-1}$	-0.01	-0.01	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Debt/TA$_{t-1}$	-0.64**	-0.64**	-0.33	-0.34
	(0.29)	(0.31)	(0.23)	(0.23)
Cash/TA$_{t-1}$	1.07***	1.10***	0.85***	0.77***
	(0.32)	(0.32)	(0.23)	(0.24)
ROA$_{t-1}$	0.92***	0.81***	0.37**	0.30*
	(0.27)	(0.26)	(0.15)	(0.15)
Fixed assets/TA$_{t-1}$	0.44**	0.41**	-0.15	-0.19
	(0.18)	(0.18)	(0.12)	(0.12)
CAPEX/TA$_{t-1}$	-1.66**	-1.47*	1.48**	1.45**
	(0.80)	(0.86)	(0.66)	(0.70)
R&D expenses/TA$_{t-1}$	6.26***	6.43***	3.99***	3.89***
	(0.58)	(0.57)	(0.35)	(0.36)
Tobin's Q$_{t-1}$	0.03	0.05**	0.07***	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
Equity/TA$_{t-1}$	-0.14	-0.08	0.10	0.12
	(0.25)	(0.26)	(0.17)	(0.18)
Public debt rating$_{t-1}$	1.69***	1.67***	1.21***	1.21***
	(0.20)	(0.20)	(0.12)	(0.12)
HHI$_{t-1}$	0.30	0.45	0.11	0.10
	(0.93)	(1.01)	(0.73)	(0.76)
HHI$^2{}_{t-1}$	0.24	0.03	0.18	0.25
	(1.19)	(1.30)	(0.94)	(0.97)
Bank concentration$_{t-1}$	-0.48**	-0.65**	-0.16	-0.24
	(0.25)	(0.27)	(0.19)	(0.21)
Bank market share$_{t-1}$	0.21	0.18	0.18	0.06
	(0.30)	(0.31)	(0.23)	(0.24)
Bank geographic diversification$_{t-1}$	0.40	0.42*	-0.09	-0.09
	(0.26)	(0.25)	(0.16)	(0.16)
Number of lending relationships$_{t-1}$	-0.00	0.02	-0.03	-0.04
	(0.03)	(0.04)	(0.02)	(0.03)
Lending relationship length$_{t-1}$	0.00	0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	31,340	26,346	31,316	26,171
Pseudo R-squared	0.72	0.72	0.37	0.36
Sector FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Sector×Year FE	No	Yes	No	Yes
State×Year FE	No	Yes	No	Yes

Note: This table shows the effect of bank specialization on firms' innovation output. 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. 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: Patents and patent citations

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.54	0.99	0.38	0.64
	(0.60)	(0.68)	(0.40)	(0.49)
Bank specialization$_{t-1}$ $\times$ Asset overhang$_{t-1}$	-1.92***	-1.61***	-1.84***	-0.90**
	(0.73)	(0.59)	(0.49)	(0.41)
Observations	26,346	26,346	26,171	26,171
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$\times$Year FE	Yes	Yes	Yes	Yes
State$\times$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 3.3. 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.

Table 5: Bank specialization and corporate innovation: Patent originality and generality

	Patent originality		Patent generality	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.03	0.04	0.01	0.02
	(0.03)	(0.03)	(0.04)	(0.04)
Observations	35,023	34,912	35,023	34,912
Adjusted R-squared	0.35	0.35	0.38	0.37
Sector FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Sector×Year FE	No	Yes	No	Yes
State×Year FE	No	Yes	No	Yes

Note: This table shows the effect of bank specialization on the novelty of firms' innovation output. In the first two columns, the outcome variable is the average originality of the patents filed by a firm in a given year. In the last two columns, the outcome variable is the average generality of the patents filed by a firm in a given year. 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 corporate innovation: Patent originality and generality

	Patent originality		Patent generality	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.04	0.04	0.02	0.02
	(0.03)	(0.03)	(0.04)	(0.04)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-0.08***	-0.06**	-0.11***	-0.09***
	(0.02)	(0.03)	(0.03)	(0.04)
Observations	34,912	34,912	34,912	34,912
Pseudo R-squared	0.35	0.35	0.37	0.37
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 originality of patents filed by a firm in a given year. In the last two columns, the outcome variable is the generality of 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 3.3. 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.

Table 7: Bank specialization and corporate innovation: Innovation survey data

	(1) Product innovation	(2) Process innovation	(3) World-first innovation
Bank specialization$_{t-1}$	-0.06	0.29	0.09
	(0.41)	(0.37)	(0.20)
Observations	15,171	15,171	12,016
Adjusted R-squared	0.25	0.31	0.09
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 8: Bank specialization, asset overhang, and corporate innovation: Innovation survey data

	(1) Product innovation	(2) Process innovation	(3) World-first innovation
Bank specialization$_{t-1}$	-0.43	0.33	-0.13
	(0.46)	(0.42)	(0.20)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-0.83*	0.09	-0.47**
	(0.43)	(0.43)	(0.23)
Observations	15,171	15,171	12,016
Adjusted R-squared	0.25	0.31	0.09
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 9: Bank specialization, asset overhang, and loan conditions

Panel A: ln(All-In Drawn Spread)	(1)	(2)	(3)
Bank specialization$_{t-1}$	0.07	-0.12	-0.06
	(0.12)	(0.17)	(0.17)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$		0.30	-0.01
		(0.21)	(0.33)
Bank specialization$_{t-1}$ × High asset overhang$_{t-1}$		-0.05	-0.26
		(0.26)	(0.31)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$ × High asset overhang$_{t-1}$		0.70*	0.71*
		(0.37)	(0.43)
Observations	18,003	18,003	18,003
Adjusted R-squared	0.71	0.71	0.71
Panel B: Pr(Covenant violation)	(1)	(2)	(3)
Bank specialization$_{t-1}$	-0.29**	-0.32*	-0.33*
	(0.15)	(0.18)	(0.18)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$		0.30	0.11
		(0.25)	(0.28)
Bank specialization$_{t-1}$ × High asset overhang$_{t-1}$		-0.77**	-0.52
		(0.38)	(0.33)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$ × High asset overhang$_{t-1}$		1.20*	0.97**
		(0.73)	(0.45)
Observations	7,943	7,943	7,943
Adjusted R-squared	0.50	0.50	0.50
Panel C: ln(Maturity)	(1)	(2)	(3)
Bank specialization$_{t-1}$	0.28***	0.30**	0.24*
	(0.11)	(0.12)	(0.14)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$		-0.31	0.26
		(0.22)	(0.40)
Bank specialization$_{t-1}$ × High asset overhang$_{t-1}$		0.10	0.23
		(0.20)	(0.21)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$ × High asset overhang$_{t-1}$		0.39	-0.82*
		(0.46)	(0.48)
Observations	19,784	19,784	19,784
Adjusted R-squared	0.42	0.42	0.42
Asset overhang measure		Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes
Firm FE	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. The outcome variable is the natural logarithm of the average loan rate (measured as the all-in-drawn spread) in Panel A, the average loan covenant strictness in Panel B, and the natural logarithm of the average loan maturity in Panel C. 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 3.3. The innovative sector dummy variable is equal to one for sectors with above-average patents, and zero otherwise. The high asset overhang dummy variable is equal to one if the corresponding measure of asset overhang is in the top tercile. 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.

Appendix

Table A1: Variable definitions

Variable	Description
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 et al. (2013).
Capital intensity	The sector-year level average of firms' fixed assets to total assets.

Table A2: Robustness: Bank mergers as a source of exogenous variation in bank specialization

	Δln(1+patents)		Δln(1+citations)	
	(1)	(2)	(3)	(4)
ΔBank specialization$^{\text{Merger implied}}$	-0.13	-0.15	-0.12	-0.12
	(0.14)	(0.19)	(0.21)	(0.30)
Observations	1,926	1,848	1,926	1,848
R-squared	0.07	0.18	0.06	0.18
Controls	Yes	Yes	Yes	Yes
Sector FE	Yes	No	Yes	No
State FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Sector×Year FE	No	Yes	No	Yes
State×Year FE	No	Yes	No	Yes

Note: This table shows effect of bank specialization on firms' innovation output, 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. 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: Bank mergers as a source of exogenous variation in bank specialization

	Δln(1+patents)		Δln(1+citations)	
	(1)	(2)	(3)	(4)
ΔBank specialization$^{\text{Merger implied}}$	-0.28	-0.27	-0.34	-0.31
	(0.23)	(0.24)	(0.35)	(0.36)
ΔBank specialization$^{\text{Merger implied}}$ × Asset overhang	-0.52*	-0.52	-0.90**	-0.81*
	(0.31)	(0.32)	(0.39)	(0.42)
Observations	1,848	1,848	1,848	1,848
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 3.3. 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.

Table A4: Robustness: Sorting

	Patents$_{[t\text{-}3,t\text{-}1]}$		Citations$_{[t\text{-}3,t\text{-}1]}$	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	1.78	-0.14	0.16	0.04
	(1.12)	(1.63)	(0.65)	(0.73)
Bank specialization$_{t-1}$ $\times$ Asset overhang$_{t-1}$	-1.57	1.68	-0.94	-0.09
	(1.17)	(1.18)	(0.66)	(0.57)
Bank size$_{t-1}$	0.66***	0.63***	-0.16**	-0.17**
	(0.24)	(0.22)	(0.08)	(0.08)
Bank deposits/TA$_{t-1}$	-4.72***	-4.83***	-1.43***	-1.43***
	(0.65)	(0.65)	(0.30)	(0.30)
Bank equity/TA$_{t-1}$	21.90***	22.05***	-0.38	-0.56
	(5.65)	(5.77)	(2.80)	(2.80)
Bank LLP/TA$_{t-1}$	34.05	36.06	16.49	18.13
	(25.89)	(25.85)	(15.53)	(15.58)
Bank ROA$_{t-1}$	-3.53	0.01	-6.28	-5.16
	(17.84)	(17.57)	(8.69)	(8.60)
Bank market share$_{t-1}$	1.79***	1.83***	0.23	0.26
	(0.48)	(0.48)	(0.29)	(0.29)
Bank geographic diversification$_{t-1}$	-0.39	-0.42	0.01	0.01
	(0.40)	(0.41)	(0.19)	(0.19)
Bank concentration$_{t-1}$	-1.01	-1.05	-0.01	-0.03
	(0.70)	(0.70)	(0.27)	(0.27)
Observations	4,040	4,040	4,040	4,040
Adjusted R-squared	0.59	0.59	0.26	0.26
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector$\times$Year FE	Yes	Yes	Yes	Yes
State$\times$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 3.3. 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.

Table A5: Robustness: Alternative channels

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Controlling for banks' sectoral zombie lending				
Bank specialization$_{t\text{-}1}$	0.59	1.07	0.36	0.63
	(0.59)	(0.67)	(0.40)	(0.49)
Bank specialization$_{t\text{-}1}$ × Asset overhang$_{t\text{-}1}$	-1.87***	-1.65***	-1.85***	-0.90**
	(0.72)	(0.59)	(0.49)	(0.41)
Bank zombie lending$_{t\text{-}1}$	-5.93***	-6.25***	0.69	0.38
	(1.94)	(1.97)	(1.55)	(1.57)
Observations	26,346	26,346	26,171	26,171
Pseudo R-squared	0.72	0.72	0.36	0.36
Panel B: Controlling for sectoral complexity				
Bank specialization$_{t\text{-}1}$	0.80	0.82	-0.65	-0.37
	(1.13)	(1.10)	(0.77)	(0.78)
Bank specialization$_{t\text{-}1}$ × Asset overhang$_{t\text{-}1}$	-1.86**	-1.63***	-1.95***	-1.03**
	(0.74)	(0.59)	(0.49)	(0.41)
Bank specialization$_{t\text{-}1}$ × Complex$_{t\text{-}1}$	-0.36	0.36	1.48	1.51
	(1.30)	(1.29)	(0.91)	(0.95)
Observations	26,346	26,346	26,171	26,171
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 3.3. Panel A includes a control for banks' (sectoral) zombie lending, as defined in Section 5.3.2. Panel B includes a control for the interaction between bank specialization and the informational complexity of a sector, as defined in Section 5.3.2. 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 A6: Robustness: Controlling for interactions between asset overhang and other bank characteristics

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.64	0.79	0.40	0.61
	(0.61)	(0.71)	(0.40)	(0.51)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-2.28***	-1.38**	-2.04***	-0.90**
	(0.78)	(0.61)	(0.51)	(0.43)
Bank concentration$_{t-1}$	-0.42	-2.28***	-0.27	-0.79*
	(0.27)	(0.62)	(0.24)	(0.44)
Bank concentration$_{t-1}$ × Asset overhang$_{t-1}$	-0.63	1.53***	0.20	0.61*
	(0.44)	(0.47)	(0.32)	(0.33)
Bank market share$_{t-1}$	0.26	0.38	0.17	0.28
	(0.30)	(0.48)	(0.24)	(0.33)
Bank market share$_{t-1}$ × Asset overhang$_{t-1}$	-0.35	-0.10	-0.67**	-0.30
	(0.48)	(0.39)	(0.27)	(0.27)
Bank geographic diversification$_{t-1}$	0.51**	0.26	-0.05	-0.12
	(0.25)	(0.38)	(0.17)	(0.24)
Bank geographic diversification$_{t-1}$ × Asset overhang$_{t-1}$	-0.40	0.06	-0.18	0.02
	(0.40)	(0.30)	(0.23)	(0.19)
Lending relationship length$_{t-1}$	0.00	-0.01	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Lending relationship length$_{t-1}$ × Asset overhang$_{t-1}$	0.01	0.02	0.01	0.00
	(0.02)	(0.01)	(0.01)	(0.01)
Number of lending relationships$_{t-1}$	0.02	0.05	-0.06**	-0.05
	(0.03)	(0.06)	(0.03)	(0.05)
Number of lending relationships$_{t-1}$ × Asset overhang$_{t-1}$	0.01	-0.02	0.09**	0.01
	(0.07)	(0.04)	(0.05)	(0.03)
Observations	26,346	26,346	26,171	26,171
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 3.3. 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.

Table A7: Robustness: Fixed effects

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Including firm fixed effects				
Bank specialization$_{t-1}$	-0.74	0.21	0.61	1.25*
	(0.56)	(0.74)	(0.58)	(0.74)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.25*	-1.63***	-1.50**	-1.34**
	(0.72)	(0.58)	(0.73)	(0.53)
Observations	9,923	9,923	9,787	9,787
Adjusted R-squared	0.86	0.86	0.43	0.43
Panel B: Including bank-by-time fixed effects				
Bank specialization$_{t-1}$	0.86	1.48**	-0.59	-0.40
	(0.62)	(0.70)	(0.71)	(0.64)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.56*	-1.45*	-1.85***	-0.76**
	(0.93)	(0.76)	(0.45)	(0.36)
Observations	15,622	15,622	15,467	15,467
Pseudo R-squared	0.75	0.75	0.41	0.40
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 3.3. 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.

ONLINE APPENDIX

Bank Specialization and Corporate Innovation

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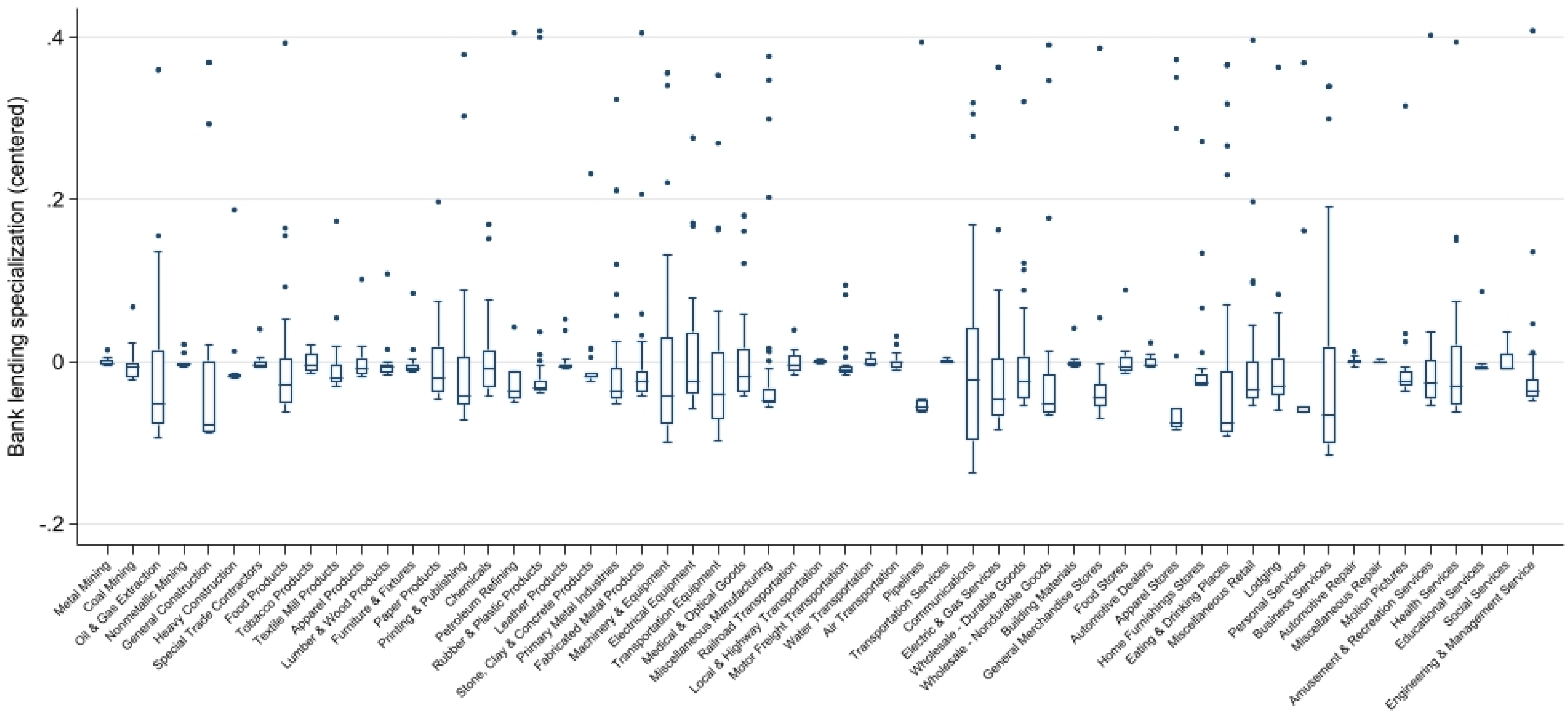
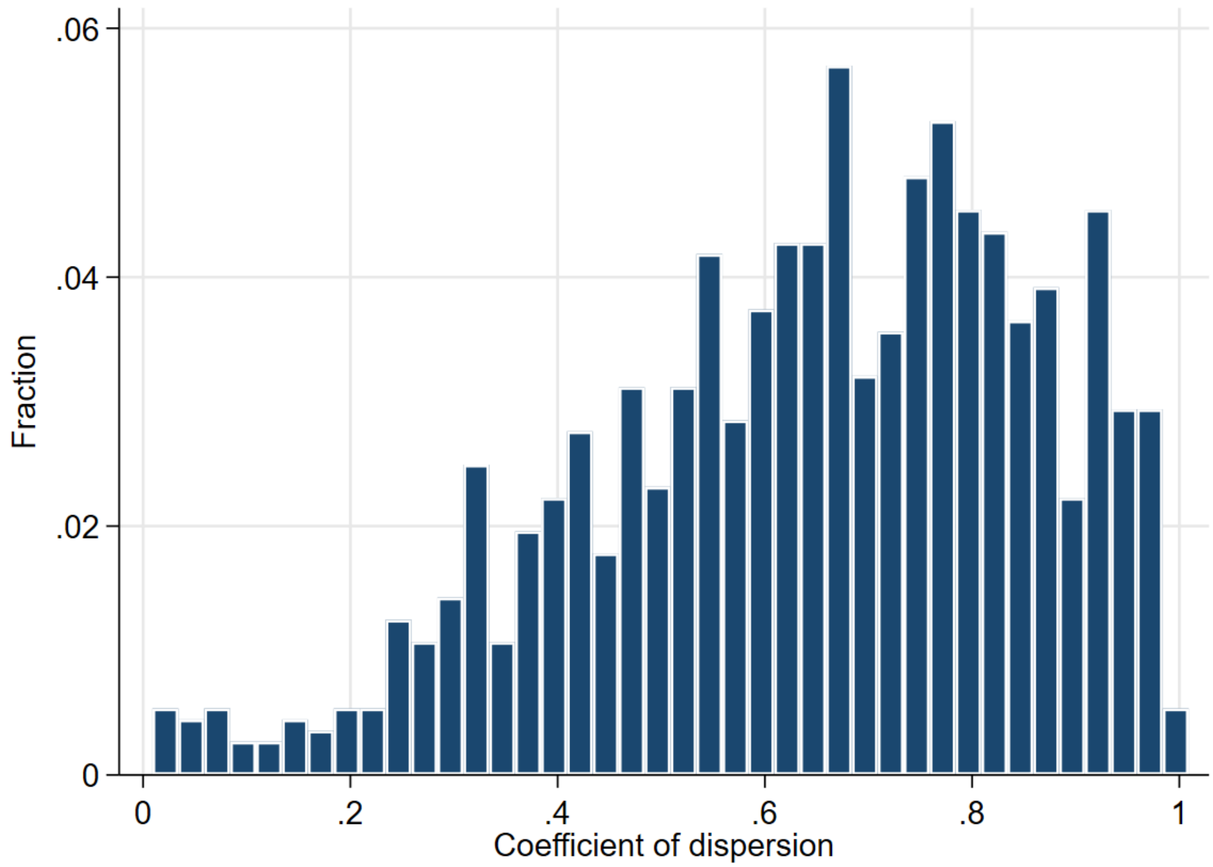
Figure O1: A box-and-whisker plot of banks' sectoral specialization across sectors



Note: This figure presents the box-and-whisker plot of bank specialization for each sector in the year 1998. The figure shows on the Y-axis the distribution of the demeaned bank specialization values and on the X-axis the corresponding (2-digit SIC) sectors. Each dot represents an outlier and, therefore, a bank that is specialized in that sector.

Figure O2: The distribution of the coefficients of dispersion of banks' sectoral specialization



Note: This figure presents distributional information on within-sector dispersion in bank specialization. For each sector and each year, we compute a modified quartile coefficient of dispersion, as the ratio of the difference and the sum of the 90^{th} and 50^{th} percentile of bank specialization. The larger the coefficient of dispersion, the larger the within sector differences in bank specialization. We compute this coefficient of dispersion for every sector and every year in the sample. The histogram shows on the X-axis bins of this coefficient of dispersion and on the Y-axis the fraction of sector-year combinations in that specific bin.

Table O1: The distribution of the number of bank relationships

Number of bank relationships	Percentage	Cumulative Percentage
1	70.79	70.79
2	22.74	93.52
3	4.92	98.44
4	1.01	99.45
5+	0.55	100.00
Total	100.00	

Note: This table presents summary statistics on the distribution of the number of (lead arranger) bank relationships per 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 O2: Summary statistics: U.S. data sample

	N	Mean	Median	SD	Min	Max
Patents	35,023	5.31	0.00	19.23	0.00	159.00
Patent citations	35,023	1.96	0.00	5.76	0.00	82.90
Patent originality	35,023	0.11	0.00	0.23	0.00	0.83
Patent generality	35,023	0.17	0.00	0.35	0.00	0.97
Size	35,023	6.55	6.54	1.86	0.33	10.26
Age	35,023	3.75	0.00	5.74	0.00	23.00
Debt/TA	35,023	0.31	0.28	0.25	0.00	1.52
Equity/TA	35,023	0.39	0.39	0.23	0.00	0.93
Cash/TA	35,023	0.08	0.03	0.10	0.00	0.80
ROA	35,023	0.00	0.03	0.20	-3.00	0.22
Fixed assets/TA	35,023	0.57	0.51	0.39	0.00	1.55
CAPEX/TA	35,023	0.06	0.04	0.06	0.00	0.25
R&D expenses/TA	35,023	0.02	0.00	0.06	0.00	0.59
Tobin's Q	35,023	0.80	0.48	1.18	0.00	11.87
Public debt rating	35,023	0.73	1.00	0.44	0.00	1.00
HHI	35,023	0.19	0.15	0.14	0.02	0.69
Bank specialization	35,023	0.06	0.03	0.08	0.00	0.46
Bank market share	35,023	0.15	0.11	0.15	0.00	0.59
Bank concentration	35,023	0.30	0.26	0.14	0.09	1.00
Bank geographic diversification	35,023	0.87	0.95	0.19	0.00	0.99
Number of lending relationships	35,023	1.37	1.00	0.72	1.00	11.00
Lending relationship length	35,023	4.19	3.00	3.10	1.00	23.00
Asset redeployability	35,023	0.00	-0.11	1.00	-1.93	2.85
Product market rivalry	35,023	0.00	-0.34	1.00	-1.12	1.94

Note: This table presents summary statistics of the main variables used in our empirical analysis. 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 O3: 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	-0.025	1.000																
(3) Debt/TA	0.075	-0.058	1.000															
(4) Equity/TA	-0.205	0.125	-0.691	1.000														
(5) Cash/TA	-0.202	0.077	-0.280	0.302	1.000													
(6) ROA	0.224	0.004	-0.164	0.178	-0.141	1.000												
(7) Fixed assets/TA	0.150	-0.043	0.160	-0.097	-0.235	0.027	1.000											
(8) CAPEX/TA	-0.034	-0.047	0.032	0.080	-0.077	0.010	0.537	1.000										
(9) R&D expenses/TA	-0.236	0.024	-0.137	0.129	0.407	-0.408	-0.158	-0.051	1.000									
(10) Tobin's Q	-0.020	0.119	-0.267	0.343	0.335	0.054	-0.121	0.023	0.240	1.000								
(11) Public debt rating	0.146	0.182	-0.196	0.209	0.075	0.096	-0.013	-0.028	0.015	0.213	1.000							
(12) HHI	0.015	0.027	-0.022	-0.006	-0.057	0.070	-0.065	-0.082	-0.104	-0.003	0.103	1.000						
(13) Bank specialization	0.004	-0.046	0.043	-0.027	0.044	-0.101	0.090	0.099	0.114	0.003	-0.084	-0.167	1.000					
(14) Bank market share	0.475	0.035	0.067	-0.132	-0.082	0.101	0.054	-0.057	-0.135	0.015	0.109	0.081	-0.127	1.000				
(15) Bank concentration	0.056	0.050	-0.034	0.022	0.001	0.045	-0.030	-0.077	-0.022	0.041	0.118	0.326	-0.141	0.218	1.000			
(16) Bank geographic diversification	0.220	0.044	0.007	-0.031	-0.034	0.057	-0.023	-0.056	-0.054	0.053	0.056	0.040	-0.243	0.346	0.067	1.000		
(17) Number of lending relationships	0.277	-0.023	0.116	-0.141	-0.108	0.031	0.059	-0.014	-0.090	-0.066	0.036	0.007	0.025	0.069	-0.051	-0.003	1.000	
(18) Lending relationship length	0.340	0.118	0.027	-0.065	-0.066	0.078	0.086	-0.053	-0.108	0.017	0.167	0.085	-0.029	0.308	0.122	0.149	0.036	1.000

Note: This table presents the correlations between the main variables used in our empirical analysis. 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: Belgian data sample

	N	Mean	Median	SD	Min	Max
Product innovation	15,171	0.39	0.00	0.49	0.00	1.00
Process innovation	15,171	0.50	0.00	0.50	0.00	1.00
World-first innovation	15,171	0.06	0.00	0.23	0.00	1.00
Size	15,171	15.59	15.46	1.68	9.93	19.25
Age	15,171	27.99	25.00	17.21	1.00	150.00
Debt/TA	15,171	0.63	0.64	0.26	0.04	2.89
Equity/TA	15,171	0.36	0.34	0.26	-1.89	0.98
Cash/TA	15,171	0.13	0.08	0.15	0.00	0.90
EBIT/TA	15,171	0.07	0.06	0.12	-0.70	0.63
Fixed assets/TA	15,171	0.24	0.19	0.21	0.00	0.96
CAPEX/TA	15,171	0.00	0.00	0.07	-0.69	0.76
R&D expenses/TA	15,171	0.02	0.00	0.08	0.00	0.65
HHI	15,171	0.05	0.02	0.07	0.00	0.69
Bank specialization	15,171	0.05	0.02	0.06	0.00	0.25
Bank market share	15,171	0.22	0.24	0.08	0.00	0.69
Bank concentration	15,171	0.23	0.22	0.04	0.15	0.83
Bank geographic diversification	15,171	0.01	0.00	0.01	0.00	0.26
Number of lending relationships	15,171	1.87	2.00	0.91	1.00	4.00
Lending relationship length	15,171	11.47	12.00	5.42	1.00	20.00
Capital intensity	15,171	0.00	-0.21	1.00	-2.14	4.33

Note: This table presents summary statistics of the main variables used in our 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 that borrow from banks active in the Belgian loan market.

Table O5: Bank specialization and contractual loan amounts

	(1) ln(Loan amount)	(2) ln(Loan amount)	(3) ln(Loan amount)
Bank specialization$_{t-1}$	1.56***	1.66***	1.57***
	(0.22)	(0.23)	(0.27)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$		-0.28	0.03
		(0.48)	(0.93)
Bank specialization$_{t-1}$ × High asset overhang$_{t-1}$		-0.29	0.06
		(0.38)	(0.40)
Bank specialization$_{t-1}$ × Innovative$_{t-1}$ × High asset overhang$_{t-1}$		-0.68	-0.43
		(1.02)	(1.03)
Observations	19,815	19,815	19,815
Adjusted R-squared	0.78	0.78	0.78
Asset overhang measure		Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes
Sector×Year FE	Yes	Yes	Yes
Bank×Year FE	Yes	Yes	Yes
Firm FE	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. The outcome variable is the natural logarithm of the total loan amount. 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 **??**. The innovative sector dummy variable is equal to one for sectors with above-average patents, and zero otherwise. The high asset overhang dummy variable is equal to one if the corresponding measure of asset overhang is in the top tercile. Variable definitions are provided in Table **??** in Appendix. Standard errors (in parentheses) are clustered at the firm level. *, ** and *** denote significance at 10%, 5% and 1%, respectively.

Table O6: Robustness: Alternative measures of bank specialization

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Bank specialization based on number of lending relationships				
Bank specialization$_{t\text{-}1}$	0.43	0.70	0.13	0.46
	(0.68)	(0.75)	(0.45)	(0.49)
Bank specialization$_{t\text{-}1}$ × Asset overhang$_{t\text{-}1}$	-1.58*	-1.15*	-1.86***	-0.98**
	(0.83)	(0.65)	(0.56)	(0.44)
Observations	26,346	26,346	26,171	26,171
Adjusted R-squared	0.72	0.72	0.36	0.36
Panel B: Bank specialization based on 3-digit SIC codes				
Bank specialization$_{t\text{-}1}$	-0.88	-0.55	0.52	0.43
	(0.83)	(0.86)	(0.51)	(0.55)
Bank specialization$_{t\text{-}1}$ × Asset overhang$_{t\text{-}1}$	-1.65*	-1.89***	-1.30**	-0.43
	(0.89)	(0.73)	(0.51)	(0.46)
Observations	20,592	20,592	20,414	20,414
Pseudo R-squared	0.77	0.77	0.37	0.37
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 O7: Robustness: Alternative lead arranger definitions

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Bank specialization based on lead arranger definition from Ivashina (2009)				
Bank specialization$_{t-1}$	0.81	1.31**	0.44	0.66
	(0.53)	(0.60)	(0.35)	(0.42)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.78***	-1.71***	-1.55***	-0.82**
	(0.64)	(0.52)	(0.42)	(0.36)
Observations	25,853	25,853	25,678	25,678
Adjusted R-squared	0.72	0.72	0.36	0.36
Panel B: Bank specialization based on lead arranger's exact loan share				
Bank specialization$_{t-1}$	0.54	1.10*	0.37	0.67
	(0.60)	(0.67)	(0.41)	(0.46)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.22	-1.46**	-1.64***	-0.85**
	(0.83)	(0.61)	(0.55)	(0.41)
Observations	24,359	24,359	24,184	24,184
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 lead arrangers are defined based on the definition of Ivashina (2009) instead of Chakraborty et al. (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 O8: Robustness: Excluding term loans B or bank-sector-time bins with less than ten loans

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Excluding term loans B				
Bank specialization$_{t-1}$	0.66	1.23	0.42	0.65
	(0.81)	(1.04)	(0.34)	(0.41)
Bank specialization$_{t-1}$ $\times$ Asset overhang$_{t-1}$	-1.65**	-1.74**	-1.53***	-0.81**
	(0.77)	(0.70)	(0.52)	(0.36)
Observations	24,209	24,209	24,035	24,035
Adjusted R-squared	0.73	0.73	0.36	0.36
Panel B: 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$_{t-1}$ $\times$ 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
Asset overhang measure	Asset redeployability	Product market rivalry	Asset redeployability	Product market rivalry
Controls	Yes	Yes	Yes	Yes
Sector$\times$Year FE	Yes	Yes	Yes	Yes
State$\times$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 term loans B are excluded from the sample. 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 bank-sector-time bins with less than then loans 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 O9: Robustness: Excluding recession periods or multiple-bank borrowers

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Excluding recession periods				
Bank specialization$_{t\text{-}1}$	0.36	0.74	0.42	0.66
	(0.61)	(0.70)	(0.41)	(0.51)
Bank specialization$_{t\text{-}1}$ $\times$ Asset overhang$_{t\text{-}1}$	-1.74**	-1.37**	-1.80***	-0.79*
	(0.76)	(0.60)	(0.51)	(0.42)
Observations	22,303	22,303	22,128	22,128
Pseudo R-squared	0.72	0.72	0.36	0.36
Panel B: Excluding multiple-bank borrowers				
Bank specialization$_{t\text{-}1}$	0.32	0.57	0.27	0.59
	(0.69)	(0.82)	(0.43)	(0.54)
Bank specialization$_{t\text{-}1}$ $\times$ Asset overhang$_{t\text{-}1}$	-1.81**	-1.08	-1.93***	-0.90**
	(0.80)	(0.68)	(0.51)	(0.45)
Observations	16,381	16,381	16,247	16,247
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$\times$Year FE	Yes	Yes	Yes	Yes
State$\times$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 O10: Robustness: Alternative clustering methods

	Patents		Citations	
	(1)	(2)	(3)	(4)
Panel A: Standard errors clustered by sector				
Bank specialization$_{t-1}$	0.54	0.99	0.38	0.64
	(0.81)	(1.03)	(0.35)	(0.48)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.92***	-1.61**	-1.84***	-0.90**
	(0.69)	(0.64)	(0.46)	(0.38)
Observations	26,346	26,346	26,171	26,171
Pseudo R-squared	0.72	0.72	0.36	0.36
Panel B: Standard errors clustered by bank				
Bank specialization$_{t-1}$	0.32	0.57	0.27	0.59
	(0.48)	(0.64)	(0.40)	(0.45)
Bank specialization$_{t-1}$ × Asset overhang$_{t-1}$	-1.81***	-1.08	-1.93***	-0.90***
	(0.57)	(0.75)	(0.38)	(0.30)
Observations	16,381	16,381	16,247	16,247
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. 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 O11: Robustness: OLS estimation

	ln(1+patents)		ln(1+citations)	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}$	0.17	0.14	0.04	0.02
	(0.14)	(0.14)	(0.12)	(0.12)
Bank specialization$_{t-1}$ $\times$ Asset overhang$_{t-1}$	-0.44***	-0.37***	-0.30***	-0.24**
	(0.12)	(0.14)	(0.09)	(0.11)
Observations	34,912	34,912	34,912	34,912
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 O12: Robustness: Alternative empirical specification

	Patents		Citations	
	(1)	(2)	(3)	(4)
Bank specialization$_{t-1}^{Low\ asset\ overhang}$	4.95*	1.57*	3.87*	1.50**
	(3.04)	(0.94)	(2.05)	(0.68)
Bank specialization$_{t-1}^{Moderate\ asset\ overhang}$	1.96**	1.07	1.37**	-0.28
	(0.82)	(1.04)	(0.61)	(0.78)
Bank specialization$_{t-1}^{High\ asset\ overhang}$	-1.59*	-1.96**	-1.06**	-0.83
	(0.83)	(0.85)	(0.50)	(0.53)
Observations	26,346	26,346	26,171	26,171
Adjusted 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. 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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