Intangible Capital and Shadow Financing

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Abstract

This paper studies corporate debt composition in an increasingly intangible economy. Using matched firm-lender corporate credit data from South Korea, we document that intangible-intensive firms disproportionately borrow from non-bank lenders. This heterogeneity in the mode of financing is amplified in response to a change in bank regulation, which acts as an exogenous tightening of bank credit supply. To make sense of these findings, we develop a model of heterogeneous firms with two types of capital and two sources of financing: regulated and shadow banks. Bank capital requirement enters the price of corporate loans directly, and raising it leads the most productive firms to both increase borrowing from non-banks, and to invest more in intangible assets.

Keywords: Corporate debt, shadow finance, intangible capital

JEL Classification Numbers: E44, E50, G21

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1 Introduction

The role of intangible capital has been steadily rising in the modern economy. By some accounts, investment in intangible assets has increased by about 50% over the last two decades (Branstetter and Sichel, 2017), and the overall stock has roughly doubled (Crouzet and Eberly, 2019). Because such assets cannot be easily used as collateral, this trend has raised concerns about firms' ability to finance investments in intangibles (Haskel and Westlake, 2018). At the same time, the landscape of financial intermediation has been shifting from traditional banks toward non-bank lenders (Lee, Lee and Paluszynski, 2024). Less onerous regulation, combined with recent technological advances in fintech, has made non-bank lenders a preferred source of credit for many firms. In this paper, we argue that the rising trends of intangible capital and shadow financing are inherently related and reinforce each other, with the link acting in both directions.

To study the debt choices of firms in an increasingly intangible economy, we use a dataset of matched firm-lender credit accounts from South Korea that includes an exogenous bank credit tightening event. We document that firms with higher intensity in intangible capital tend to borrow more from non-bank lenders, also referred to as shadow banks. Specifically, we measure the firm-level intangible capital using income statement data on expenses related to intangible investments, such as research and development and advertising. Based on this, we construct an *intangible intensity ratio*, defined as the share of intangible capital in a firm's total capital. Using our data, we show that in 2013 firms in the top quintile of intangible intensity borrowed 47% of their total credit from shadow banks, compared to 13% for firms in the bottom quintile. Crucially, this pattern intensifies over the next five years, a period of bank credit tightening in Korea induced by the implementation of Basel III — a package of more restrictive bank regulation. By 2018, the end of our sample period, the share of non-bank credit for firms in the top and bottom intangible intensity quintiles had reached 93% and 21%, respectively. While all firms increased their borrowing from shadow banks over this period, those with high intangible intensity turned more heavily to non-bank credit. A natural question that arises from these observations is: why do intangible-intensive firms borrow disproportionately more from shadow banks after the change in bank regulation?

To answer this question, we estimate the effect of Basel III — a global and plausibly exogenous reform implemented during the middle of our sample period — on the composition of corporate credit across the spectrum of firms' intangible intensity. Prior to the reform, we observe that the fraction of shadow bank credit increases uniformly over time for all firms, regardless of their intangible intensity. However, starting in 2016Q1, when the new bank regulation takes effect, a clear divergence emerges. Firms with higher intangible intensity (top quintile) choose a significantly greater share of non-bank credit, with a total expansion of 20 percentage points between 2013 and 2018. In contrast, firms with lower intangible intensity (bottom quintile) increase their share of shadow bank borrowing by only 10 percentage points over the same period. This observed rift in debt composition between tangible- and intangible-intensive firms highlights the impact of stricter bank regulation on corporate financing decisions. To quantify this divergence systematically, we run a fixed-effects regression that accounts for unobserved firm characteristics. We find that, relative to the initial differences in shadow credit share, a firm with one percentage point higher intangible intensity allocates nearly 0.15 percentage points more of its debt portfolio to shadow credit in the aftermath of the reform.

Why is intangible intensity so important for the composition of corporate credit portfolios, and which aspect of the Basel III reform drives the divergence? We posit that higher bank capital requirement—the headline component of the reform—is the primary driver of the observed divergence, operating through the firms' collateral value. To understand this mechanism, we build a simple model of firm decision making. The model consists of two periods: investment and production. Firms are heterogeneous in terms of their productivity. In the first period, firms choose a mix of tangible and intangible assets to invest in, financed through a portfolio of debt from regulated banks and shadow banks. Tangible capital exhibits the traditional features of collateralizability, slow depreciation and linear pricing. By contrast, intangible capital is assumed to have quite distinct characteristics, in line with the recent literature findings. Specifically, intangible assets are acquired at a decreasing marginal price (a flexible way of modeling high fixed costs and low variable costs), involve sunk costs (once acquired, they cannot be resold or collateralized), and depreciate rapidly. On the financing side, firms face a credit portfolio choice between senior, collateralized bank debt (subject to capital requirement regulation) and junior shadow bank debt, which incurs a search cost. In the second period, each firm draws a productivity realization and decides whether to produce or default endogenously. The key feature of our model is that the regulation parameter—a minimum capital requirement imposed on banks—explicitly enters the firms' debt pricing formula. This allows the model to incorporate a directly observable source of exogenous variation. By varying this parameter, we can conduct Basel III experiments in the model that are directly comparable to the Korean data.

The optimal firm behavior in the model displays several interesting features. First, firms with higher expected productivity endogenously choose to become more intangible intensive, consistent with the data. The key to generate this result is our assumption of a decreasing marginal price of intangible investment. Such assets are naturally more appealing to firms that expect to be more productive and to have higher output. Under our preferred parameter values, these firms also invest less in tangible assets overall, aligning with the observation that firms with the most tangible assets in Korea, such as shipbuilders or heavy manufacturers, tend to be less productive. Second, more intangible intensive firms incur higher search costs and borrow disproportionately more from shadow banks. This outcome arises from two factors. On the one hand, these firms have fewer tangible assets to pledge as collateral, making bank loans more expensive. Bank loans are expensive not only because low collateral increases the expected loss in the event of default, but also because regulatory requirements compel banks to finance a larger portion of such loans with their own equity. On the other hand, due to their larger scale and hence higher borrowing needs, intangible-intensive firms are more willing to invest in searching for a more elastic shadow credit supply, ultimately using it more.

The main quantitative experiment we conduct with our model mimics the introduction of Basel III by increasing the capital requirement variable, as specified in the actual reform. In the baseline exercise, firms across the productivity distribution shift credit away from regulated banks and towards shadow financing. Consistent with the data, this substitution is disproportionately stronger for more productive, and therefore more intangible intensive, firms. At the same time, all firms choose to invest *less* in tangible assets, as these become less useful in securing favorable interest rates from banks. As such, we find that some of the recent trend toward an increasingly intangible-intensive aggregate economy can be attributed to tighter financial regulation.

Finally, we use our model to shed some light on the effects of the reform on aggregate quantities and to conduct counterfactual exercises. We find that the baseline increase in the capital requirement leads to a modest 0.4% decline in output. The limited impact is due to the substitution of bank loans with non-bank credit that occurs simultaneously. We also design two counterfactual scenarios that produce larger effects. In the first scenario, the government acts to prevent the rise of shadow credit by administratively increasing the cost of such loans. As a result, aggregate output declines by 2% because the most productive firms in the economy face higher credit costs required to finance production, leading to reduced investment in intangible assets. In the second counterfactual, we allow intangible capital to be pledged as collateral. In this exercise, aggregate output increases by over 6%, as the most productive firms—those that invest the most in intangible assets—enjoy a significant reduction in financing costs through banks. A further decomposition shows that about 85% of this increase stems from higher recovery rates on loans in the event of default, while the rest comes from a reduced regulatory burden.

Literature review This paper builds on and connects two distinct strands of macroeconomic literature. On the one hand, it contributes to the growing body of research on the role of intangible capital in the economy. McGrattan (2020) and Crouzet and Eberly (2021) argue that accounting for intangible assets is crucial for understanding recent trends in measured productivity growth. Belo et al. (2023) use a neoclassical growth model to measure the value of intangible capital globally. Sun and Xiaolan (2019) propose that employee contracts with deferred compensation structure can incentivize intangible investments. Li (2020) and Falato et al. (2020) highlight how the exogenous shift towards intangible capital contributes to the observed corporate savings glut. Altomonte et al. (2024) use French data to argue that the availability of short-term financing, such as trade credit, enhances intangible investment. Casella, Lee, and Villalvazo (2023) demonstrate that disclosure regulation discourages intangible-intensive firms from going public. Zhang (2023) links the rise of intangibles to broader US economic trends, including changes in the labor share and business concentration. Jung (2022) quantifies the impact of general financial frictions in the context of increasing intangible capital. In relation to these papers, we emphasize the growing reliance on non-bank financial intermediation by intangible-intensive firms and argue that the rise of intangible capital may itself be stimulated by the financial environment.

On the other hand, our work relates to the role of non-bank (shadow) financial intermediaries in providing credit to firms. The rise of shadow banks, or non-bank lenders, has been extensively documented from various perspectives, including household debt (Jiang et al., 2020) and residential mortgages in the US (Buchak et al., 2018), monetary policy responses in China (Chen, Ren, and Zha, 2018), or corporate lending in the US (Chernenko, Erel, and Prilmeier, 2022) and South Korea (Lee, Lee and Paluszynski, 2024). The literature identifies two main channels driving the rapid growth of the non-bank sector: technological advances, such as fintech (Buchak et al., 2018, Jagtiani and Lemieux, 2017) and regulatory arbitrage (Plantin, 2014). While most existing studies primarily focus on changes in credit supply, we complement this literature by examining the demand for non-bank credit.

More broadly, our paper is related to the recent literature on the corporate choice between bank and bond financing. Crouzet (2018) highlights that the greater flexibility to restructure bank debt is crucial to our understanding of the trade-off between these two financing sources. Similarly, Xiang (2022) introduces a model with flexible bank debt and more rigid non-bank debt, arguing that higher capital requirement in this environment leads to a long-term decline in non-bank credit. Faria e Castro, Jordan-Wood and Kozlowski (2023) develop a model incorporating secured and unsecured debt (loans and bonds) to explain the observed spread between the two. Luk and Zheng (2022) construct a model showing how differences in the nature of contracts between secured and unsecured debt influence the borrowing firm's risk-taking behavior and explain the dynamics of these debt types over the business cycle. Relative to these studies, our work emphasizes the role of a firm's intangible-intensity profile in understanding the observed shifts in corporate credit portfolios. Finally, Lian and Ma (2021) show that a minority of debt for US firms is collateralized by assets, while most corporate borrowing is based on cash flow. Our model admits a mix of these two cases by incorporating endogenous default risk that depends on a firm's expected future cash flows.

The remainder of this paper is structured as follows. Section 2 provides background information about our data and presents the main empirical observations. Section 3 conducts our econometric analysis and discusses the results. Section 4 introduces the model of heterogeneous firms and Section 5 presents the quantitative results. Section 6 concludes.

2 Background

2.1 Data description

There are two main datasets used in this paper. The first one is a panel of firm-lender matched credit accounts of all public companies in South Korea. This data is proprietary and acquired from eCredible Co., Ltd., a major credit bureau in Korea. In this paper, we narrow our sample to non-financial corporations on the borrower side. While it is a quarterly dataset, for most of our analysis we use the annual frequency where credit information can be linked to firm level balance sheet data.[1] For the sample period of 2013-2018, we observe about 1750 firms on average, together with 315 unique lenders on

[1] For borrowers, we exclude holding companies, financial and insurance companies, and real estate companies based on their industry classifications. For the annual data, we focus on the 4th quarter data to link with the firm level balance sheet information.

average each year, which gives us a total of 60,092 firm-lender-year observations. A key advantage of this dataset is that lenders include not only commercial banks, but also non-banks such as insurance companies and wealth management companies. Throughout the paper, we refer to "bank" credit of a firm as the sum of credit extended by commercial banks[2] and "shadow" credit as the total credit extended by any lender other than commercial banks.[3] In Appendix Table 8, we provide some summary statistics of the data.

In order to study firm characteristics related to the modes of financing, we link the above credit data to a firm balance sheet dataset called KisValue. This is a widely used data source for publicly traded firms' financial as well as general information, which is developed by the National Information & Credit Evaluation (NICE) Information Service Co., a leading credit bureau in Korea. We use financial statements such as income statements and statements of financial positions in order to estimate the value of tangible as well as intangible assets and productivity at a firm level.

2.2 Construction of intangible capital and productivity

We measure intangible assets and the total factor productivity (TFP) based on the balance sheet data of each firm. In contrast to tangible assets, intangibles are typically accounted for as a stream of expenses, rather than as a stock of assets. In measuring TFP, we adopt a widely used method by Wooldridge (2009), except that we use the total capital that combines both intangible and tangible capital rather than tangible assets only in the conventional method. In what follows we elaborate on the construction of both intangible capital and TFP, and discuss potential shortcomings of our measurement. More details on the construction of our data can be also found in Appendices A.1 and B. Finally, we describe some key characteristics of the data regarding intangible intensity, productivity, and firm size.

Intangible capital We construct a stock of intangible capital for each firm based on the flow of expenses in Selling & General Administrative (SGA), which includes Research

[2]While we do observe both commercial banks and "special banks" that are directly or indirectly owned by the government, we only include commercial bank credit in our study. The reason is because special banks may extend credit to private firms based on non-market factors such as political decisions.

[3]This is a broad definition of shadow banks, encompassing a wide variety of financial institutions. The main reason why we focus on the distinction between commercial shadow banks is because a new set of bank regulation, Basel III, was applied only to the former during our sample period. As studied in more detail by Lee, Lee and Paluszynski (2024), this new regulation caused a contraction in credit supply from regulated banks while shadow banks grew in both size and significance due to the spillover effect.

and Development costs (the *knowledge capital*) as well as spending on travel, training, and promotion (the *organizational capital*). We select the detailed accounts that are closely related to these two concepts in order to exclude salaries and taxes that are usually also a part of the SGA.[4] We treat these categories of expenses as intangible investments and adopt the perpetual inventory method to recover the intangible capital stock following the common approach from the literature (Eisfeldt and Papanikolaou 2014, Falato et al. 2020). We set the depreciation rate to be 1/6 annually, based on the accounting rule that the "useful life" of patents and trademarks are 5 to 7 years. All expenses are deflated using a GDP deflator for intellectual property products.

Based on this measurement of intangible capital, we calculate the *intangible intensity* by computing the ratio of intangibles over the sum of tangible assets, which are retrieved from the balance sheet, and intangibles. In Appendix A we document a number of interesting facts regarding intangible intensity in our data. First, the distributions of intangible intensity at the beginning and at the end of our sample period, years 2013 and 2018, follow a right-skewed distribution—we find the largest mass of firms at the lowest intangible intensity, and there is a "fat tail" towards the highest intangible intensity (Figure 11). Firms tend to increase their intangible intensity in the course of our sample period, and because this measure is bounded between 0 to 1, the concentration of firms at the very top increases by 2018. While there is a clear increasing trend in the intangible intensity, we also observe substantial churning across intangible intensity quintiles over time. Figure 15 in Appendix A shows the transition probability matrix for intangible intensity by quintiles between 2013 and 2018. The majority of firms stay in the same quintile of intangible intensity over the 6 years, with a particularly strong persistence of around 70% among the firms in the top and the bottom quintile. Finally, intangible intensity is correlated with industry classifications but not perfectly. Tables 6 and 7 in the Appendix list the top 5 industries in each intangible intensity quintile using both 1-digit (broad) and 5-digit (detailed) industry classifications. In all quintiles, Manufacturing is the top broad industry—but classifying firms using a more detailed industry code, we observe that "low-tech" firms such as cardboard box manufacturers dominate the bottom quintile while "high-tech" firms such as software developers rank in the top quintile.

While the above method of using detailed accounts of SGA expenses is our benchmark

[4]The detailed accounts include: computer processing, entertainment, advertising, overseas market development, sales promotion, ordinary development, R&D costs, research costs, training, books and printing, subscription, communication, travel.

measurement of intangible capital, we compare the results with alternative measures from the literature in order to check the robustness. First, we follow Falato et al. (2020) and separately measure knowledge capital based on R&D expenses and use a more general subcategories of SGA, namely General administrative and Selling expenses, to measure the organizational capital. We find that the alternative measure of intangible intensity is highly correlated with the benchmark with a correlation coefficient of 93.2%, affirming our benchmark approach. In the Appendix Figure 12(a), we compare the two measures of intangible intensity in a scatter plot, visualizing their high correlations. Second, we compare our results with the method proposed by Eisfeldt and Papanikolaou (2014), who suggests that 30% of the aggregate SGA represent investment towards intangible capital. As the Appendix Figure 13(a) shows, our measure of intangible capital is highly correlated with the alternative method (correlation coefficient of 90%). Ours is a more conservative measure, as we use only a subset of the SGA accounts, resulting in smaller intangible intensity especially for the firms on the bottom quintile.

As a final robustness check on the intangible capital estimation, we compare the constructed measure with the book value of intangible assets. Book values of intangibles are in general less than the estimated amount of intangible capital, as the Appendix Figure 14(a) shows. In a simple OLS, book value intangible intensity is around 52% of the benchmark measure. Nevertheless, regressions show that the two measures are positively and significantly correlated.

Productivity In order to measure total factor productivity (TFP), our baseline approach adopts a Generalized Method of Moments (GMM) framework proposed by Wooldridge (2009). While we closely follow most of his setting,[5] one deviation is in including intangible capital in measuring the state variable. More specifically, we combine tangible and intangible capital in each firm, in order to create a single state variable which we call the total capital. More detailed description of the productivity measurement procedure can be found in Appendix B.

Key characteristics There are two key empirical regularities that characterize the firms in our data. First, on average, firms with high intangible intensity tend to have high productivity and are smaller in size. We use two different measures of firm size, number of employees and net sales, as well as the Total Factor Productivity described in the previous

[5]We use value added as the dependent variable, cost of sales (expenditures on intermediate inputs) as the proxy variable, wage expenditure as the variable input.

section to document robust correlations with intangible intensity across various specifications of fixed effect regressions. Table 1 summarizes the results using log net sales as the firm size measurement. Across firms within an industry, as reported in column (2) of Table 1, we find that a 1 percent increase in TFP is associated with a 0.03 pp. increase in intangible intensity, whereas a 1 percent larger firm in terms of sales tends to have a 0.016 pp. lower intangible intensity. These relationships between intangible intensity, productivity, and firm size survive even after including firm fixed effects. We find similar results using the number of employees as an alternative measure for the firm size, which are reported in Table 9 in Appendix D.

Table 1: Intangible intensity, productivity, and firm size

VARIABLES	(1) intang.intensity	(2) intang.intensity	(3) intang.intensity	(4) ln TFP
ln TFP	0.0544***	0.0305***	0.00915***	
	(0.00706)	(0.00639)	(0.00329)	
ln $Sales$	-0.0477***	-0.0155***	-0.0272***	
	(0.00416)	(0.00399)	(0.00832)	
ln $Tangible$				-0.0300***
				(0.00859)
ln $Intangible$				0.0671***
				(0.0106)
Observations	8,737	8,691	8,625	1,799
Fixed effects	Year	Yr*Ind	Yr*Ind, Firm	None
R2	0.0754	0.389	0.947	0.0220

Note: All standard errors (in parentheses) are clustered at the firm level. *** p$<$0.01

The second key observation is that productive firms tend to have fewer tangible assets and more intangible capital. In column (4) of Table 1, we take average values of log TFP, tangible and intangible assets across the sample periods for each firm and run a simple OLS regression to study their correlations. Firms with a 1% larger tangible capital are associated with 0.03% lower productivity, whereas a 1% increase in intangible assets is associated with a 0.07% higher productivity. These inverse correlations of tangible and intangible capital with productivity, together with the positive correlation of productivity and intangible intensity, are the key building blocks that will arise endogenously in our model in Section 4.

2.3 Bank and shadow credit characteristics

Regulatory measures: Basel III A defining feature of bank credit is the regulatory overhead cost — all commercial banks are subject to bank regulation, which is much stricter than the regulatory standards applied to non-bank lenders such as insurance companies and hedge funds. Furthermore, a comprehensive set of new bank regulation known as Basel III was implemented with legal penalties in 2016, tightening the bank credit supply. An increase in the minimum capital ratio requirement, which is the headline change in Basel III, was the main driver behind the decline in corporate loan provision by banks (Lee, Lee and Paluszynski 2024). In the Empirical Analysis (Section 3), we exploit this new bank regulation as a plausible source of exogenous variation[6] that directly affected banks only, and analyze the firms' financing choices in relation to their intangible intensity. Appendix E.2 contains additional details about the Basel III regulation that are important for the construction of our model of bank loan pricing in Section 4.

Credit types A key distinction between bank and shadow credit is that banks primarily originate loans, whereas shadow banks mainly purchase corporate bonds. Figure 1 illustrates the aggregate amounts of bank (left) and shadow (right) credit across three major categories: loans, bonds, and other. The "Other" category includes guarantees and other off-balance-sheet items. For banks, approximately 60 to 70% of their credit is extended through loan origination, while less than 10% comes from bond holdings. In contrast,

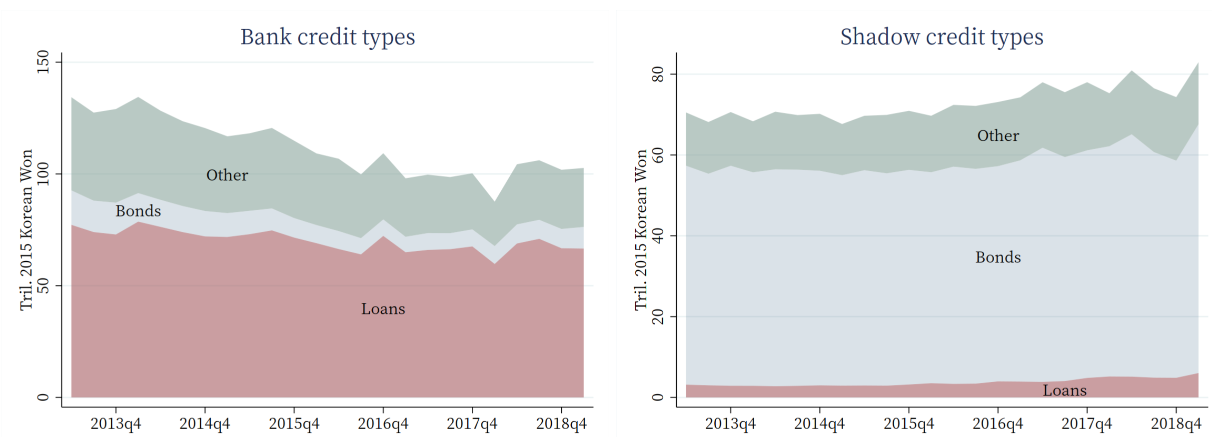

Figure 1: Bank (left) and shadow (right) credit by types

[6]The timeline of Basel III implementation was imposed by the Basel Committee on Banking Supervision, an international regulatory body. Given that the introduction of the new banking regulations was not caused by domestic economic factors, we view the regulatory reform as an exogenous event. More details can be found in Lee, Lee and Paluszynski (2024).

shadow banks predominantly hold securities rather than originating loans, with an average of 75% of their credit held in various types of bonds, including publicly and privately auctioned bonds and secondary market purchases.[7] While we do not directly observe the amount of collateral posted for each type of credit in our data, the literature supports that collateral plays an important role in bank loans (Cerqueiro et al., 2014) whereas bonds are mostly not secured in recent years (Benmelech et al., 2024). Over time, both bank loan amounts and shadow bond holdings experienced significant shifts from 2013 to 2018: bank loans decreased by 23%, while non-bank bond holdings increased by 13%.

Lender size Another distinguishing feature of regulated and shadow banks is the average size of the lenders in each group. In our data, the amount of credit extended by an average commercial bank is ten times larger than that of an average shadow bank. Banks tend to be larger and more concentrated, whereas shadow banks are smaller and more diverse in their core business models — encompassing insurance companies, hedge funds, and other entities under the term "shadow banks." Due to their smaller size and institutional heterogeneity, such institutions may exhibit a downward-sloping demand curve for corporate bonds, as studied by Koijen and Yogo (2023) and Bretscher et al. (2022). Their research indicates that insurance companies may have an inelastic demand curve with a preference for investment-grade bonds, while mutual funds display a more elastic demand curve. In Section 4, we develop a model that incorporates the potential heterogeneity among shadow banks, emphasizing that firms need to incur some cost to identify shadow banks with a more elastic supply of credit.

2.4 Aggregate intangible capital and shadow financing

We now describe the aggregate trends for intangible intensity and shadow financing using the Korean data. Figure 2 plots the two measures, based on all firms in our sample, over the time period of interest.[8] In this figure, we first observe an overall rise of both intangible intensity and shadow credit in the economy. The two measures increase steadily over the sample period, except for the latter's slight reversal in year 2018. What drives the rise in the fraction of shadow credit is simultaneously a decrease in the total amount

[7]One may suggest that we focus our study on credit type (loans versus bonds) rather than lenders (commercial and shadow banks). Since our main natural experiment is an introduction of new bank regulations, which is implemented by lenders rather than credit types, we maintain the focus of our empirical analysis on commercial versus shadow banks.

[8]Specifically, the aggregate intangible intensity is calculated by a ratio of aggregate intangible capital over the total intangible and tangible capital, while the fraction of shadow credit is equal to the ratio of aggregate shadow credit over the sum of shadow and regulated bank credit in each time period.

of regulated bank loans and an increase in the amount of shadow credit.[9] As for the intangible intensity, both tangible and intangible assets are growing in general but the growth in intangibles is faster than that of tangible assets. The reversal of the shadow credit share at the end of sample period was induced by a further change in the bank regulation that incentivized banks to extend more credit to corporate sector compared with households.[10]

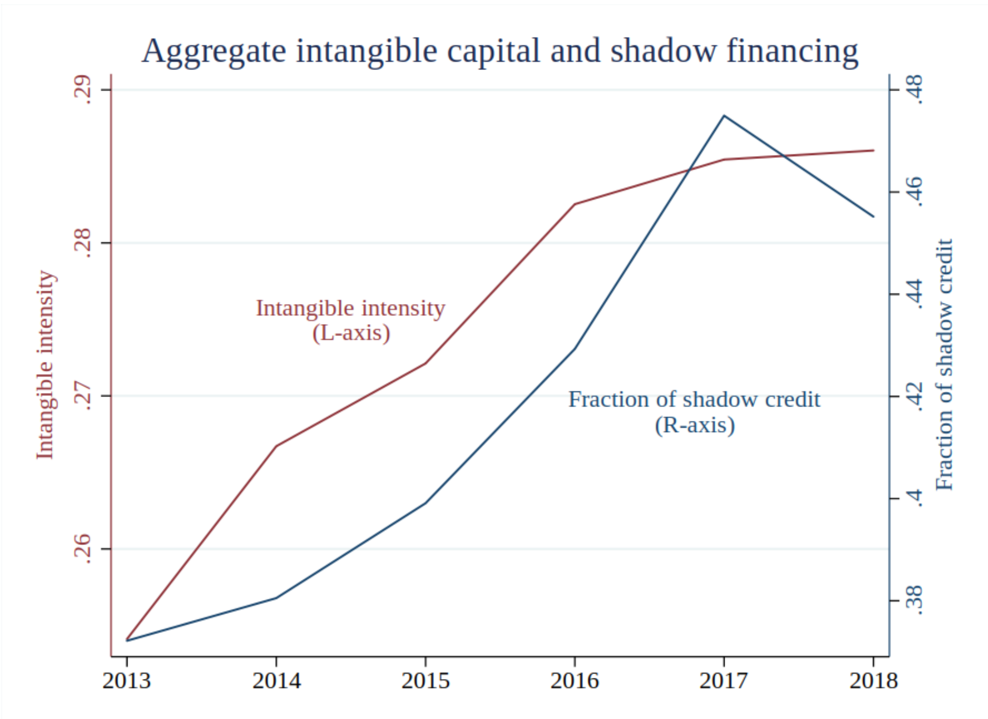

Figure 2: Aggregate intangible intensity and fraction of shadow credit

2.5 Total leverage by intangible intensity

Next, we examine changes in shadow and bank credit relative to total capital, which includes both tangible and intangible assets. Figure 3 shows the ratio of credit to total capital for each quintile of intangible intensity in 2013 (dark navy bars) and 2018 (light blue bars). In 2013, firms with relatively more tangible assets (bottom 1 to 3 quintiles) tend to have higher leverage, with the bottom quintile borrowing over 30% of their total capital compared to less than 10% for highly intangible-intensive firms (top quintile). By 2018,

[9] In Lee, Lee and Paluszynski 2024, we document these trends in more detail.

[10] Banks in Korea are subject to loan-to-deposit ratio regulations. First introduced in 2012, the ratio was calculated by dividing total loans by total deposits, assigning a uniform risk weight of 100% regardless of loan type. In 2018, the risk weights on corporate loans were reduced by 15%, while those on household loans were increased by 15%.

however, this pattern has partially reversed. While leverage has decreased for most firms, the most intangible-intensive firms (top quintile) have increased their leverage ratio to over 20%, nearly matching that of the most tangible (bottom quintile) firms. This suggests that shifts in financing modes were accompanied by changes in aggregate leverage across firms with varying intangible intensities.

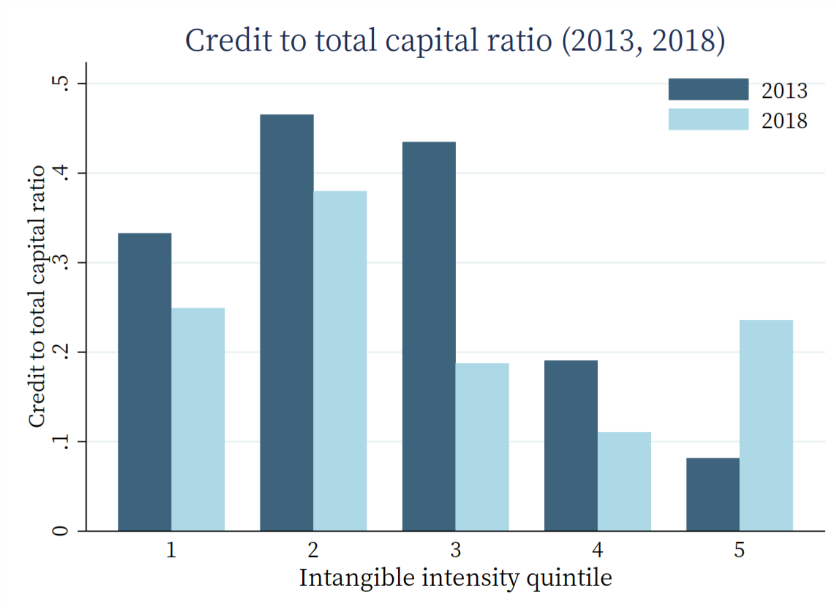

Figure 3: Fraction of credit to total capital by intangible intensity, 2013 and 2018

Note: Each credit to total capital ratio is calculated by dividing aggregate credit over the aggregate total capital within intangible intensity quintile.

2.6 Interest rates paid by lending source

While our main credit accounts dataset contains the quantities of credit only, and not the interest rates, we use alternative data sources to shed more light on the pricing of the two types of credit. The findings are presented in detail in Appendix C. The main observation is that interest rates tend to be quite dispersed across firms, and much more so for bond borrowing than for bank loans. Secondly, in 2013, the distributions of interest rates on loans and bonds mostly overlap in the run-up to the Basel III implementation, a credit-tightening event. By 2018 this is no longer true, however, with bonds displaying a clear interest rate premium over bank loans. This is an important observation that we will use as a form of external validity for the predictions of our model mechanism in Section 4.

3 Empirical Analysis

Using the data and measurements described in the previous section, we first analyze the empirical link between intangible intensity and shadow financing. Then, we formally establish the causal effect of an exogenous change in bank regulation on the borrowing patterns of firms with different levels of intangible intensity.

3.1 Shadow financing by intangible intensity

The main motivating observation of this paper is that firms with a higher intangible capital intensity tend to borrow more from shadow banks, and this trend intensifies over time. This observation is depicted in Figure 4 which plots the fraction of shadow credit, calculated as the ratio of shadow credit to total borrowing, against intangible intensity, which is the ratio of intangible capital to the sum of intangible and tangible capital.

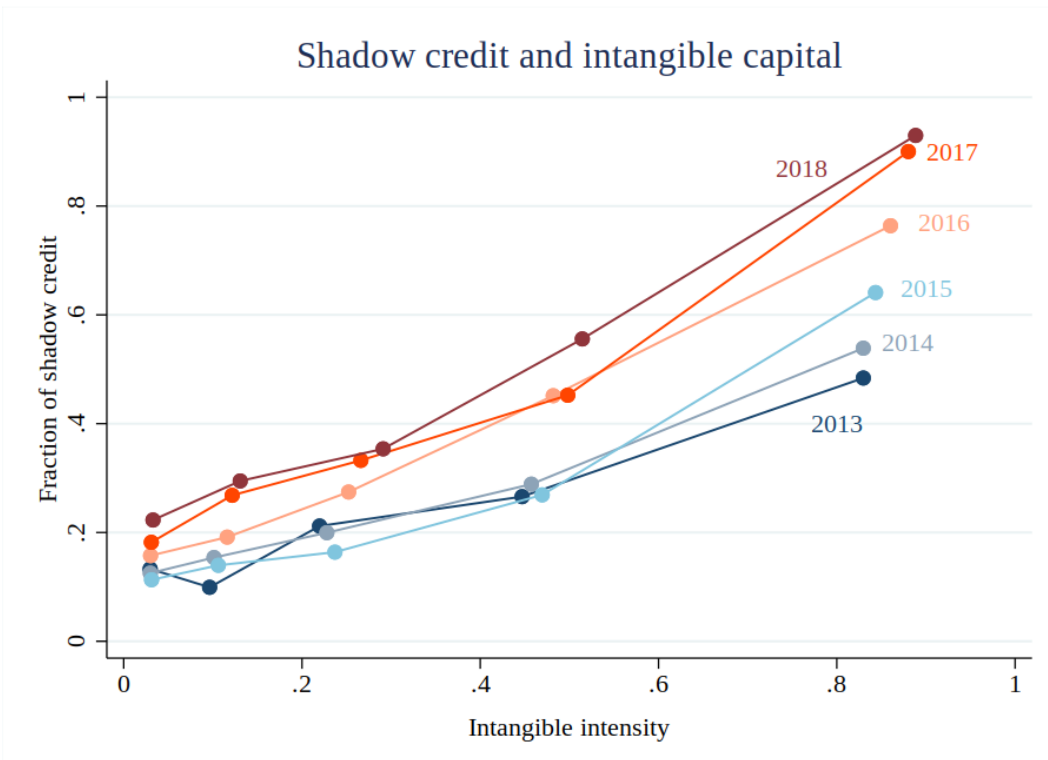

Figure 4: Fraction of shadow credit by intangible intensity

Note: Each dot is a median of intangible intensity quintile within a year.

Each line in Figure 4 features five dots that represent the medians of intangible intensity quintiles. The graph shows that in 2013, for firms in the bottom 20% of the intangible intensity distribution, the median firm has about 3% of intangible capital and borrows 13% of its credit from shadow banks. Among the top quintile, on the other hand, the median firm has much higher intangible intensity (76%) and borrows almost half (47%) of its credit from shadow banks. In 2018, which is the top maroon line, firms in all quintiles display both higher intangible intensity and higher reliance on shadow credit. However, this increase in shadow credit fraction is not uniform across firms: those with the higher intangible intensity experience a disproportionately larger increase in the fraction of shadow credit. In particular, at the end of our sample the firms in the top intangible intensity quintile borrow almost exclusively from non-banks. Figure 4 also shows that the rise in the share of shadow credit accelerates especially starting from 2016, the year when the Basel III regulation is implemented in Korea with legal penalties. This apparent cross-sectional and time series correlation between intangible intensity and the fraction of shadow financing are the central motivating observation of this paper. This pattern is also robust to alternative measures of intangible intensity, as Figures 12(b)-14(b) in Appendix A.1 show. In the quantitative part of the paper (Section 5), we recreate the predictions of Figure 4 using a formal model of firm behavior.

Next, we confirm that the observed link between intangible intensity and shadow financing is robust to controlling for other firm characteristics such as productivity, firm size, and age. In order to do so, we regress the fraction of shadow credit ($frac.shadow_{it}$) against intangible intensity ($intang.intensity_{it}$), a post-reform dummy ($post.reform_t$), which is 1 if year t is after the introduction of Basel III in 2016 and 0 otherwise, and we include its interaction with intangible intensity. We control for key firm characteristics (X_{it}) such as measured TFP, log net sales, and age. We also add the firm and industry-year level fixed effects (f_i, f_{ht}) to control for other unknown covariates. The regression specification is

$$\begin{aligned} frac.shadow_{it} = \beta_1 \cdot intang.intensity_{it} + \phi \cdot post.reform_t + \Psi X_{it} \\ + \beta_2 \cdot intang.intensity_{it} \times post.reform_t + f_i + f_{ht} + \varepsilon_{it} \end{aligned}$$

and the results are summarized in Table 2.

The estimates show that firms with high intangible intensity tend to borrow more from non-banks, and this pattern accelerates after the reform. Before the reform, columns (1) and (2) in Table 2 show that a 1 pp. increase in intangible intensity is associated with around 0.3 pp. increase in the fraction of shadow credit across firms. After the bank regulation reform in 2016, more credit is extended by shadow banks relative to traditional banks for all firms on average as the significantly positive coefficients of the *post.reform* dummy demonstrate. Moreover, this tendency intensifies especially for firms with higher intangible intensity starting from 2016, as the (*intang.intensity* $\times$ *post.reform*) interaction term shows. Finally, columns (3) and (4) demonstrate that the strong positive association between shadow credit and intangible assets survives the inclusion of firm fixed effects and (2-digit) industry $\times$ year fixed effects. In addition, the interaction term shows that within a firm, a 1 pp. increase in intangible intensity in the post-reform era is associated with around 0.1 pp. higher shadow credit fraction. This indicates that intangible-intensive firms have disproportionately gravitated towards shadow banks and away from traditional banks as their main source of credit after the reform.

Table 2: Shadow financing, intangibles, and productivity

VARIABLES	(1) *frac.shadow*	(2) *frac.shadow*	(3) *frac.shadow*	(4) *frac.shadow*
intang.intensity	0.315***	0.283***	0.148**	0.165***
	(0.0276)	(0.0325)	(0.0597)	(0.0626)
post.reform	0.0761***	0.0578***	-0.00418	
	(0.00727)	(0.0106)	(0.0111)	
intang.intensity		0.0577**	0.117***	0.0985***
$\times$ *post.reform*		(0.0281)	(0.0260)	(0.0352)
Observations	8,737	8,737	8,673	8,625
Fixed effects	None	None	Firm	Firm, Ind*Yr
R2	0.111	0.111	0.759	0.768

Note: All standard errors (in parentheses) are clustered at the firm level. *** p<0.01 ** p<0.05

3.2 Differential effects of bank regulation by intangible intensity

We now turn to analyzing our data closer to confirm that the new bank regulation indeed caused a differential borrowing behavior for firms with a varying degree of intangible intensity. Figure 5 plots the changes in the fraction of shadow credit for each intangible intensity quintile relative to the initial period (2013Q2). Firms in the bottom 20% of intangible intensity (Q1) experience a steady increase in the fraction of shadow credit throughout the sample period, culminating in a 10 percentage point rise by the end of 2018 (maroon dashed line). By contrast, firms in the top 20% of intangible intensity (Q5) exhibit an even faster growth, with their average fraction of shadow credit increasing by over 20 percentage points during the same period (solid dark maroon line). Crucially, this divergence in the reliance on shadow credit begins only in 2016Q1, coinciding with the implementation of the new bank regulation with legal enforcement. Prior to the reform, all firms show a parallel increasing trend in the share of shadow credit. Furthermore, the increase in shadow credit is more pronounced for firms with higher intangible intensity. While the gap between Q1 and Q3 is approximately 5 percentage points in 2018, it reaches 10 percentage points between Q1 and Q5. As a mirror image of this finding, the bottom three lines in Figure 5 depict the fraction of bank credit.[11]

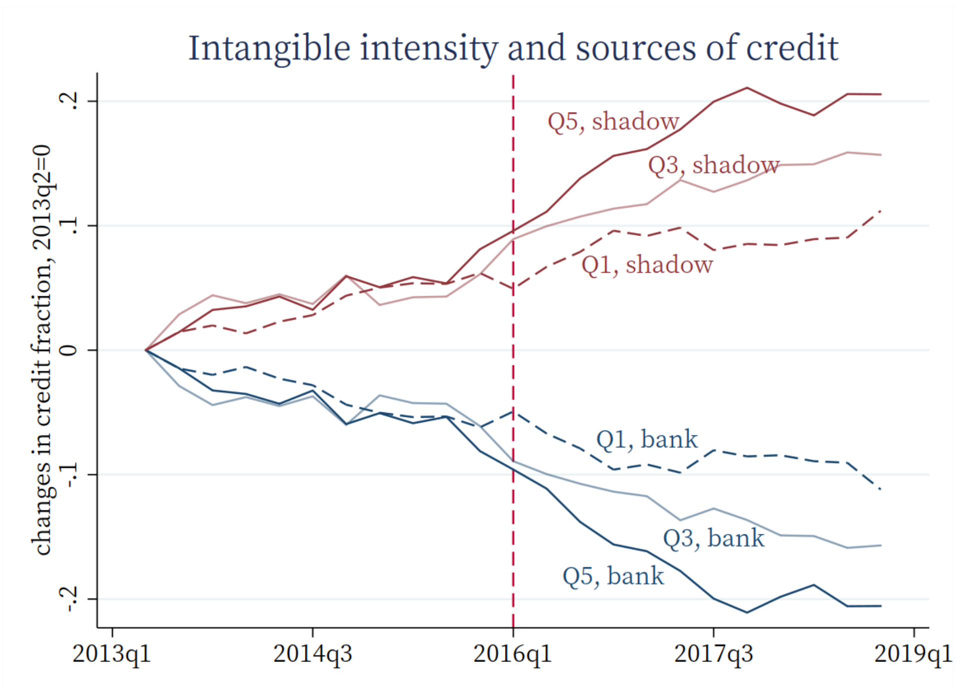

Figure 5: Changes in the fraction of bank and shadow credit by intangible intensity quintile over time

Note: Three upper maroon lines are the fraction of shadow credit, a simple average across firms within each intangible intensity quintile and quarter. Each line is normalized to 0 in 2013Q2 by subtracting the initial level. The bottom three navy lines are the fraction of bank credit, constructed analogously as the shadow credit fractions.

We measure this divergence in the mode of financing triggered by the new bank regulation by conducting a difference-in-differences regression analysis. Specifically, we regress

[11] To describe the construction of Figure 5 in more detail, the fraction of shadow (bank) credit is calculated as the amount of shadow (bank) credit over the total bank and shadow credit. Each line is a simple average across firms within each quintile of intangible intensity for each quarter. All lines are normalized to 0 in 2013Q2 by subtracting the initial level, allowing for a comparison of changes across intangible intensity quintiles. By construction, the fraction of bank credit is a mirror image of the shadow credit fraction.

the fraction of non-bank credit on lagged (year-on-year) intangible intensity, incorporating firm fixed effects to account for any unobserved firm-specific characteristics. To implement this, we first select the firms that borrow at least once in both the pre- and post-reform periods (before and after 2016Q1). This sample selection ensures that we correctly measure the treatment effect of bank regulation compared to the pre-reform period. Most of firms (96.5% out of 1,826 firms) indeed borrow in both periods. Second, we use an intangible intensity ratio lagged by 4 quarters to avoid any concurrent responses of intangible intensity to the change in bank regulation. Formally, we run the regression:

$$frac\_shadow\_credit_{it} = f_i + \beta_t + \gamma_t \cdot intangible_{i,t-4} + \Psi X_{it} + \varepsilon_{it} \tag{1}$$

where f_i is the firm fixed effect and β_t is the time fixed effect. The right-hand side variable $intangible_{i,t-4}$ represents the lagged (year-on-year) level of intangible intensity and $frac\_shadow\_credit_{it}$ is the fraction of shadow credit, both used in the previous section. The key coefficient of interest, γ_t, is the interaction term between the lagged intangible intensity and time. This term captures the *additional* changes in the fraction of shadow credit for firms with higher intangible intensity, beyond the common time trend in shadow financing captured by β_t. Lastly, a vector of control variables such as lagged (year-on-year) total factor productivity and age of firms are included in X_{it}.

Figure 6 summarizes the estimation results for the interaction term γ_t from equation (1). Relative to the initial period (2014Q2),[12] a one percentage point increase in intangible intensity is associated with approximately 0.12 to 0.16 percentage point rise in the fraction of shadow credit by the end of the sample (2018Q4). Crucially, the interaction of intangible intensity with the fraction of shadow credit becomes statistically significant only starting from 2016Q1, as marked by the dashed vertical line, coinciding with the implementation of the new bank regulation with legal enforcement. It is important to emphasize that these are additional effects beyond the average increase in the fraction of shadow credit for all firms, which adds up to approximately 7 percentage points by the end of the sample period. The estimation results for the time interaction term (β_t) are described in Figure 19 in Appendix D.

To summarize, the bank regulation reform induced a divergence in the mode of financing across firms. As the last step of our empirical analysis, we generalize this result by run-

[12] Since we are using 4-quarter lagged intangible intensity on the right hand side, the earliest period available is 2014Q2.

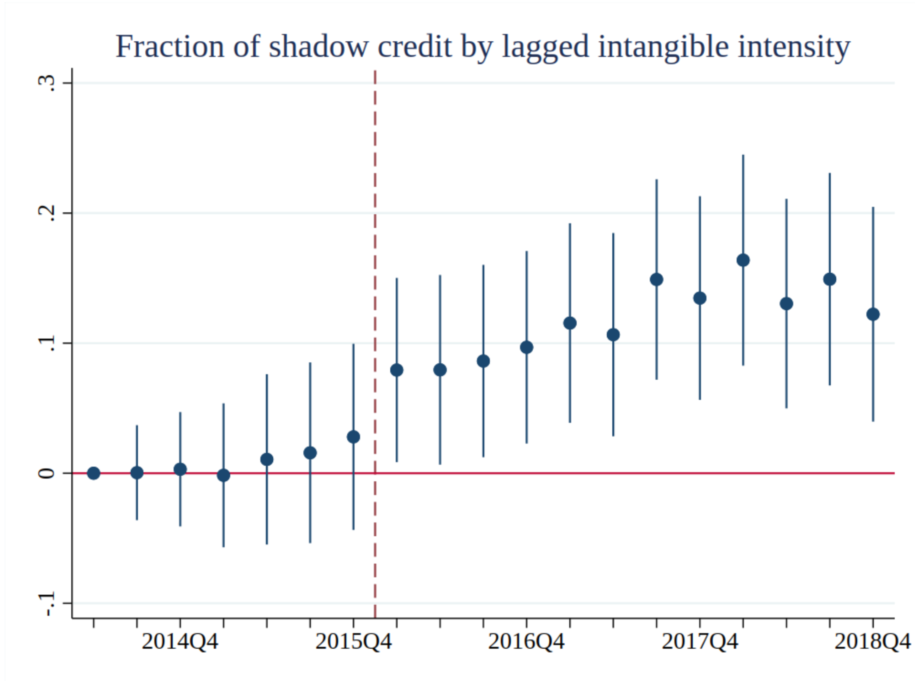

Figure 6: Changes in the fraction of shadow credit by lagged intangible intensity

Note: The initial sample period (2014Q2) is set as baseline. Standard errors are clustered at the firm level.

ning an analogous regression that uses the initial level of intangible intensity, rather than lagged levels, as an explanatory variable. The results still hold with similar magnitudes of point estimates and overall patterns. We find that firms with a 1 percentage point higher initial intangible intensity experienced 0.12 to 0.14 percentage point increase in the fraction of shadow credit post-reform. This result is shown in Figure 20 in Appendix D. As the final robustness check, we omit the lagged total factor productivity from the control variables (Figure 21) and replace lagged intangible intensity with the lagged total factor productivity (Figure 22) in Equation 1. The benchmark results are robust to omitting productivity from the control variables. On the other hand, we do not find a statistically significant response around the time of bank regulation reform once we replace the main interaction term with productivity. This additional exercise shows that it is the intangible intensity, rather than the variables correlated with it such as TFP, that explains the extent of shadow financing choice among the firms in our sample.

4 Model

In this section we develop a two period model of heterogeneous firms who seek to make capital investments in order to produce. Firms are heterogeneous ex-ante – each carries a permanent and a temporary productivity type – as well as ex-post by receiving a shock to their temporary productivity in the second period. In the first period, each firm chooses an optimal mix of tangible and intangible assets and finances this purchase from two sources: banks or non-bank (shadow) lenders. Firms may endogenously default and must compensate their lenders ex-ante for this risk. There is no aggregate uncertainty.

4.1 Environment

Timing There are two time periods, $t = 0, 1$.[13] Period $t = 0$ is the investment period where firms raise funds and make investment in their future productive capacity. Period $t = 1$ is the production period where firms use their installed capital and newly realized productivity to produce and repay their debts.

Objective There is a continuum of heterogeneous firms with a unit mass in the economy who differ in the level of their initial temporary productivity z_0, as well as the permanent productivity type ξ.[14] They seek to maximize the expected value of production net of the financing costs.

Production technology We assume that every firm has access to a production function $f\Big(\xi, z, x(k, n)\Big)$. The technology first transforms k units of physical capital and n units of intangible capital into x units of effective capital according to the CES production function

$$x = \Big[\psi n^{\nu} + (1 - \psi)k^{\nu}\Big]^{1/\nu} \tag{2}$$

where ν and ψ are the elasticity of substitution and the intangible capital share parameters, respectively. The total capital is then used to produce the final good according to the decreasing returns to scale technology

$$f(\xi, z, x) = \xi z x^{\alpha} \tag{3}$$

[13] Because the model features a dual portfolio choice—between tangible and intangible assets, and between regulated and shadow credit—we focus on solving it in a single-decision environment. While extending it to infinite horizon is potentially feasible, it would come at the expense of reduced tractability.

[14] We introduce permanent types to account quantitatively for the large dispersion in firm outcomes in the data. These types can be interpreted as introducing a form of sectoral heterogeneity.

We also assume that, in order to produce, firms must pay a fixed operating cost f_c. This feature is useful to generate firm exits in the model.

Idiosyncratic uncertainty The temporary productivity z is uncertain for each firm and depends on the predetermined initial level z_0 according to the following stochastic process

$$log\, z = \rho log\, z_0 + \sigma \varepsilon \tag{4}$$

where ρ is the persistence and σ is the standard deviation of the innovation to the process.

Tangible capital Firms can invest in tangible assets k which are characterized by mostly traditional features. Each unit of such capital costs p_k to buy and sell, and its value can be used as collateral for a loan. Tangible assets are also subject to depreciation given by parameter δ.

Intangible capital The other component of the firm's productive capacity is the intangible capital. We assume the cost to install a stock n of intangible assets is $p_n n^{\varphi}$, with $\varphi < 1$. In other words, the marginal price of each unit of intangible capital is decreasing, consistent with the literature arguing that intangible assets require a large investment in fixed cost (represented by R&D expenses, advertising, etc.) and can often be scaled at negligible variable cost (for example software can be reused and distributed freely).[15] Another key feature of intangible capital is that the investment is sunk. It cannot be recovered by the lenders and hence cannot be used as collateral. For simplicity, we also assume that intangible assets depreciate fully in the productive process.

Bank borrowing To finance their investments, firms can borrow from a bank. Banks are competitive and risk neutral; hence they must be compensated for expected losses in the event of a default. Bank loans ℓ are senior in the case of a default, but they are also subject to regulatory overhead.

Borrowing from shadow banks In addition to banks, a firm can also borrow an amount b from shadow banks. Such obligations are junior in bankruptcy proceedings, but they can also bypass bank regulation and potentially come at a lower interest rate. However,

[15] See Crouzet et al. (2022) for an overview on the economics of intangible capital. We model the intangible investment using a concave function rather than a line with positive intercept (such as $f_n + p_n n$) because it is more flexible and admits a wider range of realistic applications. For example, large firms can produce additional units of intangible capital for less than a single pre-determined parameter (p_n), while small firms can still produce some intangible capital even if they cannot afford the full pre-determined fixed cost (f_n).

there is a friction: firms must incur a monetary search cost s in order to find non-bank providers with an attractive credit supply curve. This is based on the observation that shadow banks are more numerous and on average smaller than a typical regulated bank in Korea. Therefore, borrowers face a less elastic non-bank credit supply curve (Lee, Lee and Paluszynski, 2024).[16]

Bank regulation We assume that bank loans are funded mostly with deposits that are financed at the baseline risk-free interest rate r^*. However, capital requirements mandate that banks fund a portion of their investments with their own equity. We assume the opportunity cost of bank equity is $r^{**} > r^*$. This rate can represent the fact that equity is more risky and bankers and their owners have access to higher-return investment opportunities than typical deposit holders. They also operate at a scale and are better diversified to take advantage of such opportunities.

Liquidation and default If the value of producing is negative in period $t = 1$ then no production takes place and the firm defaults. In such case, creditors recover a portion of the value of tangible assets net of fraction λ which can be thought of as deadweight loss. The proceeds are redistributed among the creditors in the order of seniority.

[16] The assumption of an imperfectly elastic non-bank credit supply curve is not essential for the main story of this paper. Without it, however, the model is prone to knife-edge behavior. The inclusion of a search friction allows us to generate reliable interior solutions, and we calibrate its parameters to fit the pre-reform data. This assumption is also supported by recent empirical studies in corporate finance which show that firms face downward-sloping demand curves for their bonds (Koijen and Yogo 2023, Bretscher et al. 2022).

4.2 Firm's problem

Optimization Given a permanent productivity type ξ and an initial temporary productivity level z_0, a firm solves the following optimization problem

$$\max_{k,n,b,\ell,e,d\geq 0} \quad d + \frac{1}{1+r^*}\mathbb{E}_{z|z_0} \max\Big\{V, 0\Big\} \tag{5}$$

$$s.t. \;\; d = -\, p_k k \underbrace{-p_n n^{\varphi}}_{\substack{\text{intangible}\\\text{investment}}} \underbrace{+q_{\ell}(k,n,b,\ell,e)\ell}_{\text{bank "loans"}} \underbrace{+q_b(k,n,b,\ell,e)b}_{\text{non-bank "bonds"}} \quad \underbrace{-s(e)}_{\substack{\text{non-bank credit}\\\text{search cost}}} \tag{6}$$

$$V = \xi z x^{\alpha} + (1-\delta)k p_k - \ell - b - f_c \tag{7}$$

$$x = \Big[\psi n^{\nu} + (1-\psi)k^{\nu}\Big]^{1/\nu} \tag{8}$$

$$log\, z = \rho log\, z_0 + \sigma\varepsilon \tag{9}$$

$$s(e) = \theta_0 e^{\theta_1} \tag{10}$$

In the first period, a firm's portfolio problem consists of choosing investments in tangible (k) and intangible (n) assets financed by bank (ℓ) and non-bank (b) debt. As we document in Lee, Lee and Paluszynski (2024), bank debt can be associated with loans while non-bank debt can be thought of as targeted bond issuance. While tangible capital is priced linearly, intangible capital features a decreasing marginal price of investment due to its fundamental characteristics discussed in the preceding section. To attain a decreasing marginal intangible investment price, we assume $\varphi < 1$.

The firm must also choose a level of search cost to secure shadow bank credit. The choice variable e, which can be thought of as elasticity of the non-bank credit supply curve, enters the firm's budget constraint as an argument of the search cost function $s(e)$ with two parameters. Ultimately, the residual from period $t = 0$ optimization is a dividend amount d which shows up in the firm's objective. Under reasonable assumptions no positive dividend will be paid, and we also exclude the possibility of external equity issuance in the form of negative dividend.[17]

In the second period, the firm's temporary productivity is realized and either production takes place or the firm defaults and exits. If the firm value is positive then the firm receives output, sells undepreciated physical capital, repays the debt and pays the fixed operating cost f_c.

[17]This assumption can be relaxed and is not crucial for our analysis.

Debt prices Both creditor types are assumed to be perfectly competitive and risk neutral; hence all debt pricing is actuarially fair. The bank and non-bank credit are distinct by their relative seniority order and by their funding costs. The debt prices are as follows

$$q_\ell(k,n,b,\ell,e) = \frac{1 - \overbrace{\mathbb{E}_{z|z_0}(V<0)}^{\text{default probability}} \left[1 - \min\{ \overbrace{\frac{(1-\lambda)kp_k}{\ell}}^{\text{loan recovery ratio}}, 1\}\right]}{1 + r_\ell(k,n,b,\ell,e)} \tag{11}$$

$$q_b(k,n,b,\ell,e) = \frac{1 - \mathbb{E}_{z|z_0}(V<0)\left[1 - \min\{\frac{\max\{(1-\lambda)kp_k - \ell, 0\}}{b}, 1\}\right]}{1 + r_b(b,e)} \tag{12}$$

As formula (11) shows, bank loans are collateralized with tangible assets and hence enjoy seniority in the recovery proceedings in the event of a default. A fraction λ of tangible capital is destroyed in the process and can be interpreted as deadweight loss.[18] The resulting liquidation value is divided equally among all bank creditors. If banks are fully repaid and anything is still left then shadow bondholders are entitled to split it equally among themselves, as equation (12) demonstrates.

Equation (12) also shows that the non-bank cost of capital depends on the elasticity variable e. Specifically, the funding cost is assumed to take the following form

$$r_b(b,e) = r^*(1+b)^{1/e} \tag{13}$$

The supply curve for non-bank credit slopes upwards and the firm's choice can be thought of as choosing an elasticity of the supply curve (as it gets large, e is approximately the constant elasticity of supply). The harder the firm searches–incurring a larger monetary cost–the better the shadow banks it encounters and the more elastic the supply curve it faces. In the limit, as $e \to \infty$, the non-bank credit supply is perfectly elastic and any quantity can be provided at the deposit interest rate r^*. The same thing happens when no shadow credit is provided in equilibrium ($b = 0$). If no search cost is incurred at all then any positive amount of non-bank credit would be infinitely expensive.

Bank regulation Equation (11) shows that the banks' cost of capital depends on the choice variables from the firm's problem. This is due to the fact that banks face minimum capital requirements. This means they cannot simply channel their depositors' funds at

[18]Notice that formulas (11) and (12) do not include the depreciation rate δ. This is because the firm's exit happens without any production taking place and hence the physical capital does not depreciate.

the marginal cost of r^*. Instead, the regulators require them to have "skin in the game" of their own. In this paper, we do not delve into the question of what the benefits of such regulation are and what the optimal degree of the banks' own investment is. Instead, we show that capital requirements can be incorporated in reduced form in the banks' pricing equation to provide a source of exogenous variation in the model, in line with the reform we study in the Korean data.

To see how the regulation enters equation (11), we first define a bank's capital ratio

$$CR = \frac{\sum \ell_i - D}{\sum \ell_i \omega_i} \tag{14}$$

where i indexes asset classes (one of which is corporate debt, our object of interest), ℓ_i and ω_i are the total investment in asset class i and the risk weight associated with it, while D represents total deposits in the bank. Suppose the opportunity cost of the banker's capital is $r^{**} > r^*$. The following lemma characterizes the bank's cost of capital.

Lemma 1 *The cost to finance a marginal unit of bank loan while keeping the capital ratio constant is*

$$\begin{aligned} r_\ell &= \omega_j CR r^{**} + (1 - \omega_j CR) r^* \\ &= r^* + \omega_j CR (r^{**} - r^*) \end{aligned} \tag{15}$$

Proof: Appendix E.1.

To provide an extra unit of loan from asset class j without affecting the measured capital ratio, the bank incurs a cost of capital that is effectively a weighted average between the deposit rate and the opportunity cost of its own equity. The weight $\omega_j CR$ is the product of the current capital ratio requirement and the risk weight assigned to the given asset class by regulators multiplied by the current level of the capital ratio. In practice, risk weights depend on observable factors such as the firm's default probability and the amount of collateral. A highlight of this approach is that the policy variable CR provides an exogenous variation in the model and allows us to conduct an analogous experiment as the one we see in the data.

To calculate the risk weight ω_j for corporate bank loans, we follow the formula set by the Basel system closely. Appendix E.2 lays out the details of this calculation. In a nutshell, the risk weight depends on the amount of collateral posted by the firm via a fraction of the loan amount forfeited, the *loss given default* (LGD). We associate LGD with the value of a firm's physical collateral relative to its bank liability in the model, and we posit a decreasing mapping between the two using a logistic function with an inflection point ι and a smoothing parameter η. Finally, the risk weight also positively depends on the firm's probability of default.

We solve the model numerically by posing a nested sequence of optimization problems. Given the choice of $(k, n, a = b + \ell, e)$, the default probability is fixed and the financing portfolio (b, ℓ) is pinned down by maximizing the revenue from debt issuance. We calculate the expectations using Gaussian quadrature with 81 nodes.

5 Numerical Analysis

In this section, we propose a parameterization for our model and characterize the numerical solution to it. We then conduct a series of experiments that aim at simulating the Basel III reform in Korea, as well as some simultaneous counterfactual scenarios.

5.1 Parameterization

Table 3 lists the parameter values we use to quantify the model. As is standard in the literature, we adopt some parameters from existing studies or external data, and we resort to a joint moments-matching exercise or educated guesses for others. Specifically, we target the cross-sectional distribution of the firms' investment decisions in period $t = 0$.

To start, we find the parameters of the autoregressive process for firms' productivity by running the corresponding fixed effects regression in our data.

$$\log(z_i) = f_i + \rho \log(z_{i,0}) + \sigma \epsilon_i \tag{16}$$

We then use the estimated values of ρ and σ which are 0.29 and 0.55, respectively, in the model. We also use the distribution of the estimated fixed effects f_i to parameterize the permanent productivity types. Specifically, we assume there are five permanent productivity types ξ and we set them equal to the fixed effect values associated with the 5th, 25th, 50th, 75th, and 95th percentiles. The corresponding mass of the permanent types is distributed with the probabilities of 0.1, 0.3, 0.2, 0.3, 0.1, respectively. Finally, because the median f_i value in the data is -0.32, we also add a constant $\mu = 0.96$ to shift the entire

Table 3: Calibrated parameter values

Parameter	Meaning	Value	Parameter group
p_k	Price of tangible assets	0.64	Investment parameters
p_n	*Price of intangible assets*	0.08	
φ	Return to intangible investment	0.70	
α	Returns to scale	0.36	Technology parameters
ν	Elasticity of substitution	0.80	
ψ	*Intangible share*	0.30	
δ	Tangible capital depreciation	0.08	
f_c	*Fixed operating cost*	0.19	
ρ	Persistence	0.29	Productivity parameters
σ	Standard deviation	0.55	
r^*	Deposit interest rate (%)	1.64	Debt pricing parameters
r^{**}	*Cost of bank capital (%)*	18.85	
λ	Deadweight loss from default	0.10	
θ_0	*Slope parameter*	0.008	Search cost parameters
θ_1	*Curvature parameter*	3.79	
CR	Capital requirement	0.08	Bank regulation parameters
ι	*LGD inflection point*	0.43	
η	LGD smoothing parameter	5	

Note: Parameters described in *italics* are calibrated in a joint moments-matching exercise. The attained matching quality can be evaluated from Figure 10 and Table 4. The remaining parameters are selected independently, as described in the main text.

distribution to the right. The shift is calibrated to prevent firms from exiting already in the first period, which could happen in the presence of the fixed cost if permanent productivity is low enough.

To guide the selection of some of the remaining parameters, we use the data observations documented in Table 1 and the following lemma.

Lemma 2 *Consider a simplified version of the model described with formulas (5)-(10) with no collateral value of tangible capital, i.e. where* $\frac{\partial q_\ell}{\partial k} = \frac{\partial q_b}{\partial k} = 0$. *The following condition assures that the optimal quantities of tangible and intangible assets are inversely correlated.*

$$\frac{\partial k^*}{\partial n^*} < 0 \iff \varphi < \nu \tag{17}$$

Proof: Appendix E.1.

Lemma 2 uses a simplified version of our model to provide a condition on the parameter values where the optimal quantities of tangible and intangible assets are inversely correlated with respect to the initial productivity. Specifically, in Table 1 we document a crucial empirical regularity in Korea that tangible capital is negatively correlated, and intangible capital is positively correlated, with firm's productivity. To embed this feature in our model, we seek a parameterization where $\varphi < \nu$.[19] Because the existing literature does not provide much guidance for these two parameters, and because we do not want to venture into extremities (where the two types of capital become almost perfect substitutes, or the acquisition of intangibles involves a too highly nonlinear cost), we settle for an intermediate case of $\varphi = 0.7$ and $\nu = 0.8$, and we perform some sensitivity analysis around these values.

We furthermore set the price of tangible assets, p_k, to 0.64 which is the average price level of capital stock relative to the price level of consumption for Korea over 1957-2019 according to the Penn World Table. The returns to scale value, $\alpha = 0.36$, the depreciation rate for tangible capital, $\delta = 0.075$, and the depositor interest rate, $r^* = 0.0164$, are adopted from our related study (Lee, Lee and Paluszynski, 2024). The deadweight loss of default, $\lambda = 0.1$, is the value estimated by Hennessy and Whited (2007). The smoothing parameter of the LGD schedule is set to an intermediate value of 5 (Appendix E.2). The initial regulation parameter is set to 8% which corresponds to the Basel II minimum total capital ratio requirement for banks.

The remaining seven parameters are found in a simple moments-matching exercise. These parameters include the price of intangible assets p_n, the intangible capital share in production function, ψ, the fixed operating cost f_c, the opportunity cost of bank capital r^{**}, the two parameters of the search cost function, θ_0 and θ_1, as well as the inflection point of the loss given default schedule, ι (Appendix E.2). These parameters are identified by targeting seven moments related to firms' decision making in the initial period. Specifically, we target the five medians of the quintiles of intangible intensity (average over years 2013-2015 in Figure 4), as well as the two regression coefficients from the regression of the fraction of shadow financing on intangible intensity (using quintile medians in years 2013-2015). We choose these targets so that the model replicates the decisions of firms before the Basel III reform in the cross section in terms of their intangible capital profiles and the corresponding financing portfolio. We achieve a good fit to the targets as

[19] While we are unable to prove this exact condition for the full version of our model, where capital also affects the firm's financial outlook, we observe that Lemma 2 nevertheless holds in that setting.

evidenced in Figure 10 and Table 4. The calibrated parameter values are reasonable; in particular, the opportunity cost of banks' capital amounts to 19%, the inflection point of the LGD schedule is around 0.4, and the non-bank credit supply search cost is small in level but also exhibits high convexity.

5.2 Model mechanisms

This section describes some intuition behind the basic mechanisms of the model. We start with a solution that can be thought of as "pre-Basel III", with the capital requirement parameter $CR = 8\%$. Figure 7 presents the policy functions for firms conditional on their initial productivity z_0 for a fixed level of permanent productivity.

Who becomes intangible-intensive? The top row panels of Figure 7 show that firms who expect to be more productive invest more in intangible capital and less in tangible assets. Consequently, they end up with a higher total effective capital x and higher intangible intensity. This result follows from assuming a decreasing marginal price of intangible investment. Because of this fundamental feature of intangible capital, scale of investment matters and firms with a larger overall production and a higher borrowing ability (that is, the more productive ones) invest more. It is also notable that such firms invest overall less in tangible capital, which is a feature of Korean data where the companies with most tangible assets such as shipbuilders or heavy manufacturers tend to be less productive (in line with the prediction of Lemma 2). At the very bottom of the initial productivity distribution, we also have the firms who choose a corner solution and forgo investing in intangible capital altogether. Among these firms, investment in tangible assets increases with initial productivity.

Who borrows from shadow banks? The bottom row panels of Figure 7 show that more productive and more intangible-intensive firms borrow a disproportionate fraction of their debt from shadow banks. This result is driven by two forces. First, such firms have fewer tangible assets and face a higher interest rate from the regulated banks due to the fact that their liabilities are mostly not backed by a collateral. Second, because of their increased borrowing ability, intangible-intensive firms are willing to incur a higher cost of searching for a more elastic shadow credit supply curve and hence they end up borrowing more from that source (Figure 9f.).

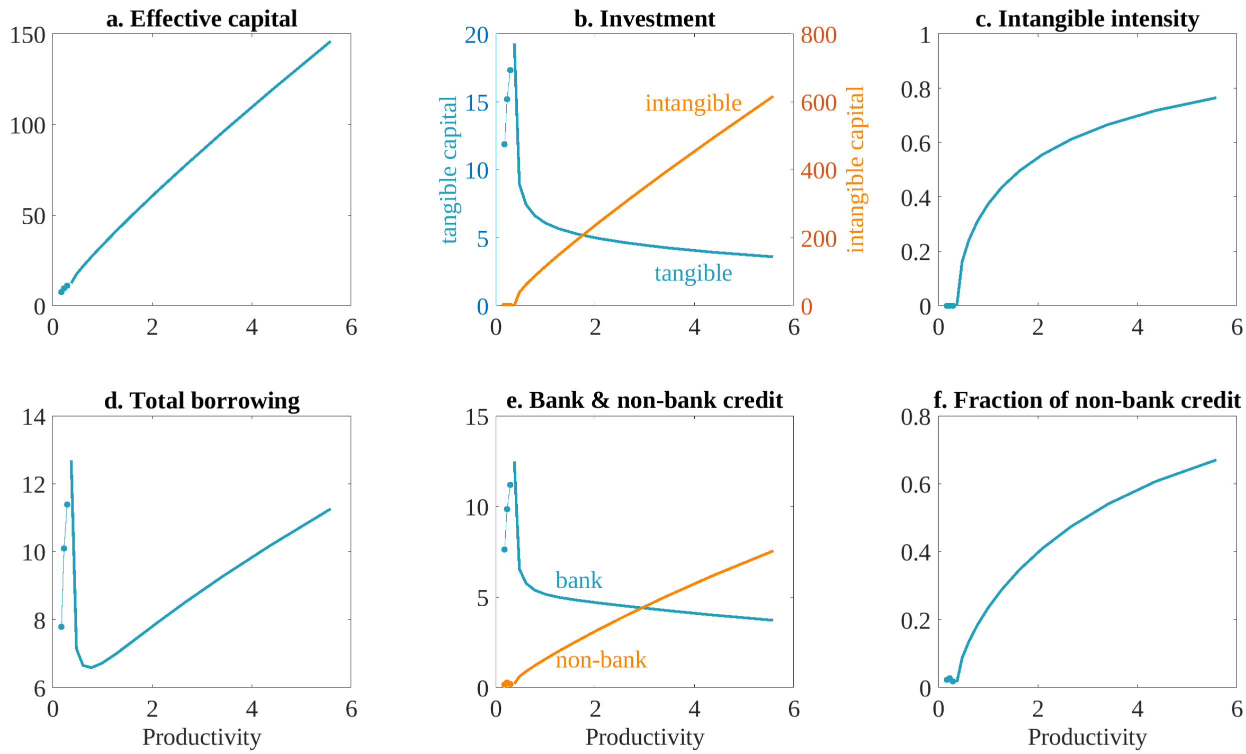

Figure 7: Model solution by initial productivity: "before Basel III" (CR=8%)

Note: The plots depict functions of initial temporary productivity z_0 for a fixed permanent type. Solid thick lines represent policy functions of firms who choose an interior solution for intangible assets ($n > 0$). Markers connected by thin lines represent policy functions of firms who choose a corner solution ($n = 0$).

5.3 Effects of higher bank capital requirement

We now use the policy lever in our model to conduct a Basel III reform experiment where we compute the model solution under a higher CR parameter in formula (15).[20] Figure 8 plots the firms' optimal decisions in a world with a higher capital requirement and contrasts them with the baseline ones. As is evident, all firms reduce their total borrowing because credit becomes more expensive, in line with the evidence on a credit crunch in Korean economy from Figure 3. Yet, the decline in total borrowing also masks an underlying substitution away from regulated banks and towards shadow banks. More productive firms substitute more for the same reasons that lead them to borrow more from shadow banks in the first place, as explained in Section 5.2. To secure a more elastic non-bank credit supply curve, they incur a higher search cost (Figure 9f.). As a result,

[20]The baseline parameter value is assumed to be 8%, which corresponds to the minimum total capital ratio under Basel II. Basel III raised this requirement to 10.5% for all banks, with an additional 1 percentage point for the largest, Domestic Systemically Important Banks (D-SIBs). Because such banks provide a vast majority of all bank loans, we assume that the post-reform requirement amounts to 11.5%.

the fraction of non-bank borrowing expands at all levels of productivity. Intriguingly, the reform also causes the more productive firms to invest less in tangible assets and hence to become more intangible-intensive. This is because, as a result of the regulatory reform, bank credit has become more expensive for any level of collateral and highly productive firms have less incentive in skewing their investment mix to secure a lower bank interest rate. This result implies that some of the increase in the aggregate intangible intensity observed in Figure 2 can actually be attributed to the financial reform. Despite this shift in the composition of firms' investment, the changes to the total installed capital x are minor (with a maximum deviation within 1%), with the largest ones experienced by the most productive firms. In Section 5.4 we show that this results in a fairly small impact of the reform on aggregate production (in line with the dynamics of the Korean economy over this time period), but not necessarily so in a counterfactual scenario in which the government prevents the expansion of the shadow banking sector.

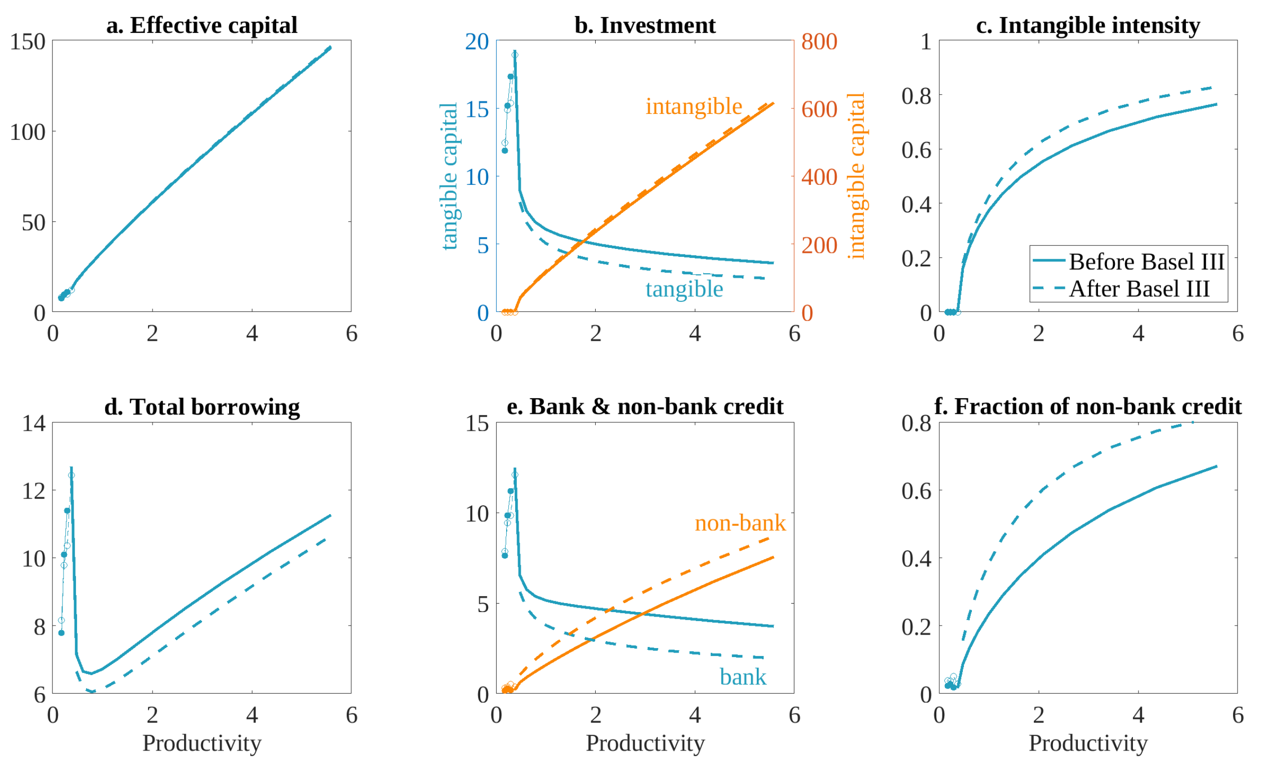

Figure 8: Model solution by initial productivity: "after Basel III" (CR=11.5%)

Note: The plots depict functions of initial temporary productivity z_0 for a fixed permanent type. Solid (dashed) thick lines represent the before-reform (after-reform) policy functions of firms who choose an interior solution for intangible assets ($n > 0$). Markers connected by thin lines represent policy functions of firms who choose a corner solution ($n = 0$).

Figure 9 plots the equilibrium credit spreads and their determinants in the "before-" and "after-" reform scenarios. More productive firms incur higher bank spreads which is partly driven by the higher cost of capital that the bank must raise to lend to them in order to comply with the regulation (panel b.), and partly because the expected recovery rate for such loans in the event of default declines with productivity due to lower collateral (panel c.). More productive firms also pay higher shadow bank spreads which is caused by the fact that they face a higher default probability (panel f.). In addition, due to the large overall volume of borrowing, they face a higher cost of non-bank capital (panel e.) even though these firms incur a higher search cost (panel f.). When the capital requirement increases, firms invest more in searching for an attractive non-bank credit supply and the bank loan recovery rates improve while spreads decline. The most productive firms turn disproportionately towards the non-bank sector and as a result enjoy the largest easing of bank financing terms, but at the same time they further deteriorate their non-bank credit conditions with higher borrowing from that source.

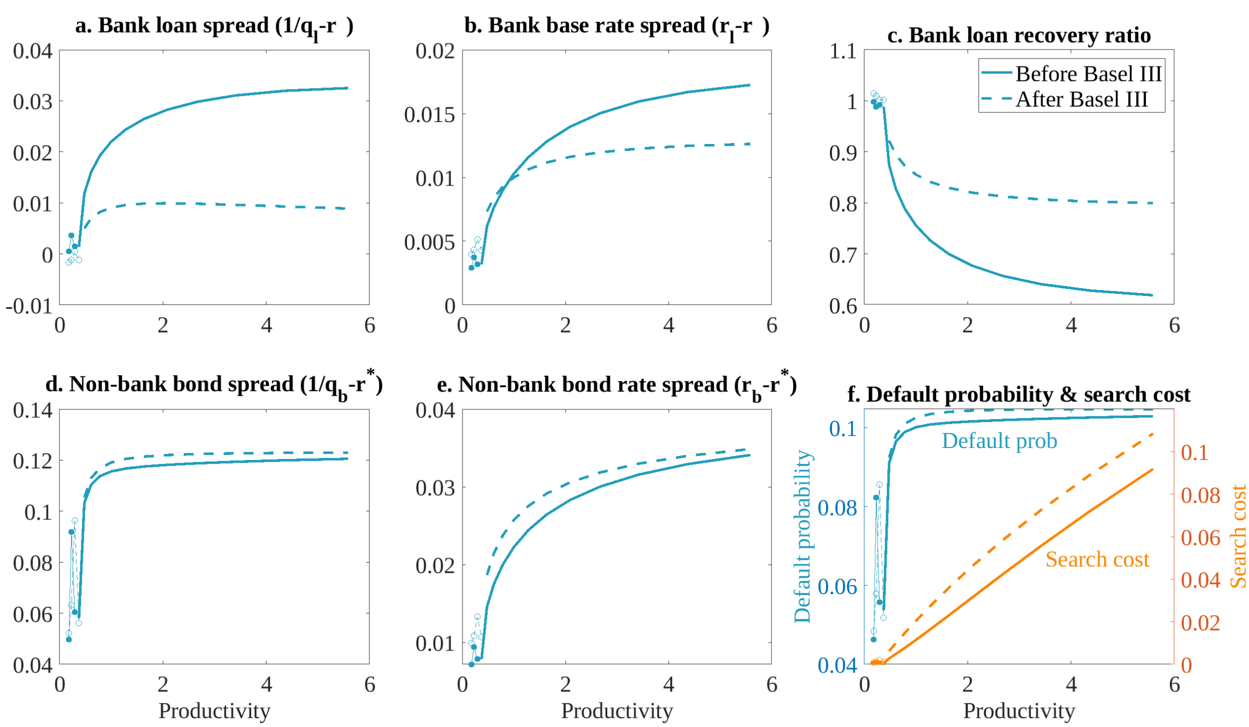

Figure 9: Prices in the model by initial productivity z_0: "before" and "after" Basel III

Note: The plots depict functions of initial temporary productivity z_0 for a fixed permanent type. Solid (dashed) thick lines represent the pre-reform (after reform) price functions of firms who choose an interior solution for intangible assets ($n > 0$). Markers connected by thin lines represent price functions of firms who choose a corner solution ($n = 0$).

While it is challenging to get a simple model such as ours to match the price levels exactly, the baseline predictions align with our observations on actual interest rates in Korea presented in Appendix C and summarized in Section 2.6. First, interest rates are quite dispersed across firms with different ratings, especially so for non-bank credit via bond issuances. This is also true in our model (panels a. and d. of Figure 9). More importantly, we observe that in the course of Basel III implementation the average bond interest premium over bank loans increases, and this is also a key result of the reform in our model, driven by the forces described in the previous paragraph.

Figure 10 plots the share of non-bank credit as function of intangible intensity quintiles, a direct counterpart to our main motivating Figure 4. The line labeled "Before Basel III" is targeted and roughly corresponds to the 2013-2015 observations in the data – more intangible intensive firms rely disproportionately on shadow financing. The line labeled "After Basel III" shows that the increase in the capital requirement causes both an upward upward shift in the fraction of shadow financing across productivity, as well as an increase in the slope of the line. While each quintile borrows a disproportionately higher share of their credit from non-banks, it is particularly true for the top quintile which post-Basel III attains a share of 85%. This aligns with the observations on the top quintile in the data. It is also notable that the median intangible intensities in all quintiles are higher after the reform than before, similar to what we observe in Figure 4. In our model, this happens endogenously as the collateral value of tangible capital falls.

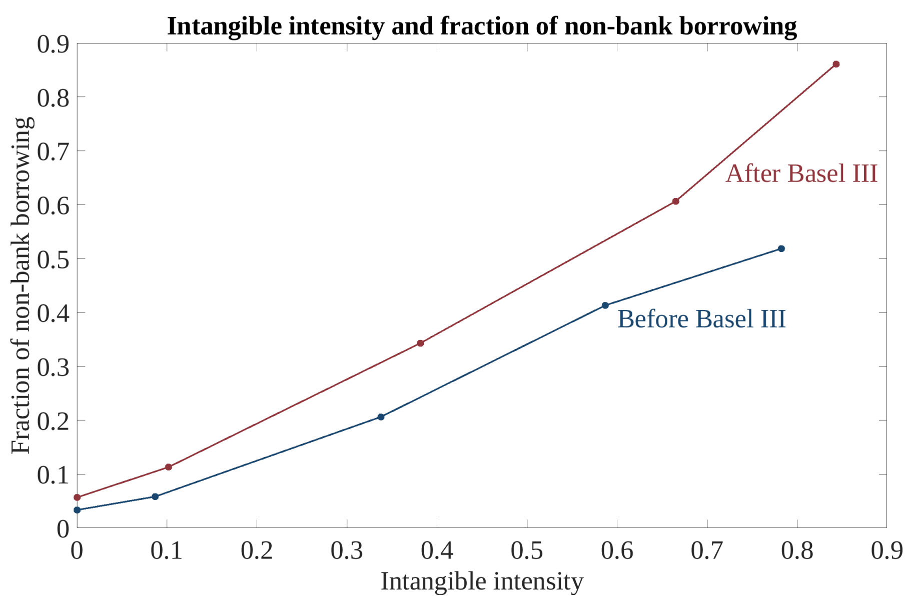

Figure 10: Shadow bank credit and intangible intensity in the model

Table 4 formalizes this result by presenting the estimated coefficients in a regression of the shadow credit share on intangible intensity at the quintile level, in the data and in the model, before the reform and after. The before-Basel III estimates are targeted and hence the model comes close to matching the empirical ones. Crucially, the post-Basel III estimates are a non-targeted outcome of the model and they still come close to the data.

Table 4: Targeted and non-targeted regression results

	Before reform *(targeted)*		**After reform** *(non-targeted)*	
Regressor	Data	Model	Data	Model
constant	0.07	0.05	0.07	0.02
intangible intensity	0.56	0.51	0.82	0.93

5.4 Aggregate effects and counterfactuals

We now turn to evaluating the aggregate effects of the reform under different scenarios by calculating the aggregate output, investment and credit in period $t = 1$. Table 5 shows a negative output change in the basic Basel III reform scenario of -0.4%. While the reform exacerbates the financial friction, firms are mostly able to mitigate the effects of it by substituting the more expensive bank credit (a 33% reduction) with shadow financing (a 75% increase) across the productivity spectrum. As a result, they are able to sustain a mostly unchanged level of production. Under the hood of the decline in output, we observe an 11.5% decline in tangible assets, along with a 1.2% increase in intangible capital.

As a final piece of the analysis, we evaluate two counterfactual scenarios. In the first one, along with the baseline increase in the capital requirement, the government also tries to counteract the rise of shadow financing by affecting the search cost parameter to prevent the shift in the credit supply curve.[21] This experiment is motivated by the fact that the recent rise of shadow banking has been perceived by many as an unwelcome force and a potential threat to financial stability.[22] In the second counterfactual, we analyze a scenario in which a system is created to allow using intangible capital as collateral in bank

[21]Specifically, we increase the search cost slope parameter θ_0 to 0.02 while keeping the curvature parameter θ_1 unchanged relative to the baseline reform. This increase is calibrated to minimize the change in the fraction of shadow financing line in Figure 7 relative to the before reform one.

[22]See e.g. "Shadow Banks Need Regulation to Rein in Financial Risks", *Bloomberg*, November 1 2019; or "The clean-up of the non-bank sector needs to begin now", *Financial Times*, April 19 2020.

Table 5: Aggregate effects of the reform under different scenarios

Model	**Output**	**Tangible assets**	**Intangible assets**	**Bank credit**	**Shadow credit**
Before Basel III	100.00	57.22	2292.31	52.60	18.72
% change:					
After Basel III	-0.41	-11.52	1.21	-33.11	74.67
+No rise of non-banks	-1.93	14.54	-4.76	6.28	0.79
+Intangible collateral	6.31	-26.89	33.99	-25.44	55.93
$\Longrightarrow$ recovery only	4.68	-22.55	26.10	-42.10	105.32
$\Longrightarrow$ regulation only	1.04	-15.21	6.72	-19.20	32.06

Note: The top row quantities are normalized relative to output. The numbers in subsequent rows represent percent changes relative to each corresponding level in the top row ("Before Basel III"). The "recovery only" row refers to the variant of the "Intangible collateral" scenario where the value of intangibles only enters the actual loan recovery rate and do not affect the regulatory function. The "regulation only" is the other case where the value of intangibles only enters the regulatory function but not the actual recovery rate of the lenders.

borrowing. Specifically, we use average intangible intensity in Korean data to back out a hypothetical linear price of intangible assets, and then we include the intangible assets valued in this way in the bank recovery function. To remain somewhat conservative, we only allow 50% of all intangible assets valued in this way to be posted as collateral. While not a policy recommendation per se, this scenario aims to mimic actual policy proposals from various countries with an aim to create an institutional setting for pledging certain intangible assets such as patents or software as collateral.[23] Detailed analysis of the policy functions for these two counterfactuals can be found in Appendix E.3.

The last four rows of Table 5 summarize the change in output and other aggregates under the two counterfactuals. In the no-rise-of-shadow scenario, output declines by almost 2%, magnifying the effect obtained under the baseline experiment where shadow banks are allowed to expand freely. The decline stems from a 5% reduction in investment in intangible capital along with a reduction in borrowing from both sources. This result highlights the potential pitfalls of restricting the flow of credit to the most productive firms in the economy.[24] Nevertheless, this loss is dwarfed by the gain in output of over

[23]For example, South Korea has a policy of supporting intellectual property-backed financing through the Korean Intellectual Property Office (KIPO). The policy provides guarantees for repurchasing of many such loans in default up to 50% of the defaulted value.

[24]Naturally, there are potential benefits to financial stability from regulating the shadow bank activity. We do not delve into this side of the trade-off in the present paper and focus on measuring the potential

6% in the scenario where half of the value of intangible capital can be posted as collateral. This gain is powered by a large-scale substitution from tangible to intangible assets and from bank credit to shadow credit. To decompose this effect, we also experiment with the reform where the collateralized value of intangible capital only shows up either in the lenders' loan recovery rate, or in the regulatory function r_ℓ. In both cases we observe that investment in tangible assets declines and in intangible capital rises. Firms move away from bank credit and increase their borrowing from shadow banks. The difference shows up in the relative sizes. Most of the effect arises quantitatively from boosting the recovery rates of loans to intangible intensive firms, while only about 1 percentage point of the total 6% increase in output comes from the sheer easing of the regulatory burden.

6 Conclusion

In this paper we use micro evidence from corporate credit accounts in South Korea to document that firms who use more intangible capital in their production tend to borrow from shadow banks more than traditional firms. We further document that this difference becomes wider during the period of credit tightening such as the introduction of the Basel III bank regulation.

We explain these findings using a simple model of heterogeneous firms who choose their capital structure and have an option to borrow from shadow banks. An attractive feature of the framework is that the regulation parameter directly enters a debt pricing formula allowing us to conduct realistic policy experiments. We find that higher bank capital requirements cause the most productive firms to invest more in intangible assets and finance this investment with higher borrowing from shadow banks. Our results suggest potentially significant efficiency gains from creating an institutional setting in which intangible assets can be collateralized.

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A Intangible capital

A.1 Measurement

Data We use KisValue data in measuring intangible capital. For the sample of listed non-financial firms ("Manufacturing", KIS010) on three stock exchanges (KOSPI, KOSDAQ, KONEX), we use the following variables:

- SELLING & GENERAL ADMIN. EXPENSES (124000)
  - organizational capital: General administrative expenses (124200), Selling expenses (124300);
    Computer processing (124227), Entertainment (124311), Advertising (124312), Overseas market development (124318), Sales promotion (124319), Training (124223), Travel (124211), Books & printing (124221), Subscription (124219), Communication (124212).
  - knowledge capital: Research costs (124406), Ordinary R&D cost (124410), Ordinary development (124420)

FKSS 2020 In the first alternative approach, we build knowledge capital and organization capital separately. Knowledge capital ($KC_{i,t}$) is constructed based on the sum of three expenses ($RnD.exp_t$): Research costs (124406), Ordinary R&D cost (124410), and Ordinary development (124420).

$$KC_{i,t} = (1 - \delta_k)KC_{i,t-1} + \frac{RnD.exp_t}{gdp.def_t}$$

Following Falato et al. (2020), we set $\delta_k = 0.15$. When the detailed accounts of research and development expenses are missing, we impute with 0. Organization capital is calculated using the same formula as in the benchmark, with one exception. SGA expenses are now equal to the sum of General administrative expenses (124200) and Selling expenses (124300), which are subcategories of SELLING & GENERAL ADMIN. EXPENSES (124000). Any missing observations are imputed with 0. Initial capital stock is set equal to the starting year expenses, which is year 2010 or listed year, whichever comes later.

EP 2014 In the second alternative approach, we use SELLING & GENERAL ADMIN. EXPENSES (124000) to build the organization capital. For the stock of organization capital in firm i and time t, we closely follow Eisfeldt and Papanikolaou (2014):

$$O_{i,t} = (1-\delta)O_{i,t-1} + \theta \frac{SGA_{it}}{gdp.def_t}$$

where SGA_{it} is SELLING & GENERAL ADMIN. EXPENSES (124000), $gdp.def_t$ is GDP deflator, and parameters are set as $\delta = 0.2$ and $\theta = 0.3$. The reason why only a fraction of SGA expenses counts is because they include other expenses that are less relevant to the organization capital, such as bad debt expenses. Initial capital stock is set equal to the starting year expenses, which is year 2010 or listed year, whichever comes later.

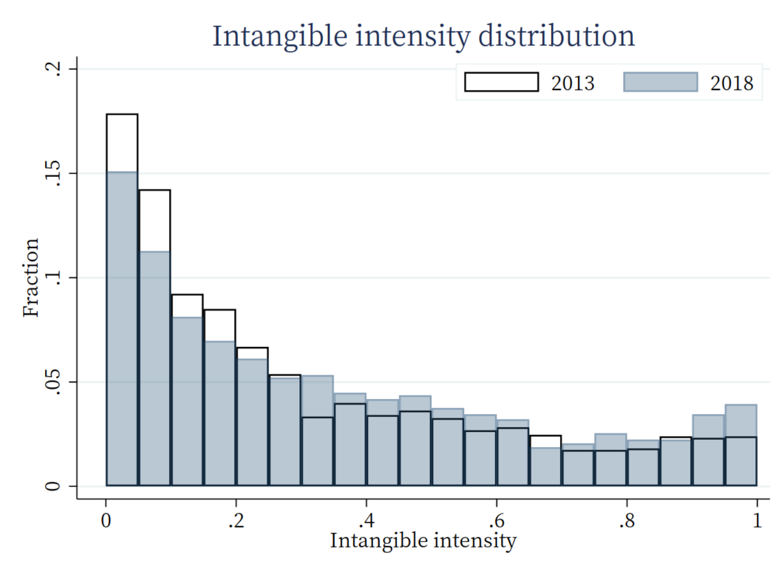


Figure 11: Distribution of intangible intensity, 2013 and 2018

Book value Book value of intangible assets is collected from Statement of Financial Position, TOTAL INTANGIBLE ASSETS (113400). All values are deflated with the GDP deflator from Bank of Korea.

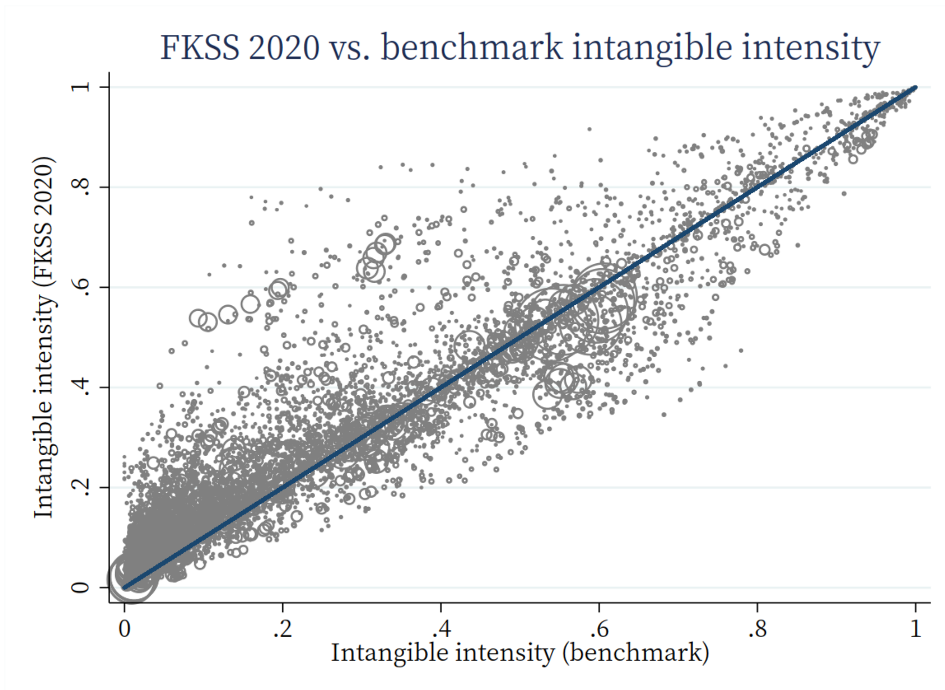
Comparison of intangible intensity measures Both alternative and book value measures are highly correlated with the benchmark approach, as Figures **??** to 14(a) show. Alternative measures tend to be larger than the benchmark, especially for the companies at the bottom intangible intensity quintile. Book values are often closer to 0, and much smaller than the benchmark estimation for most cases.

Table 6: Top 5 industries by intangible intensity quintiles

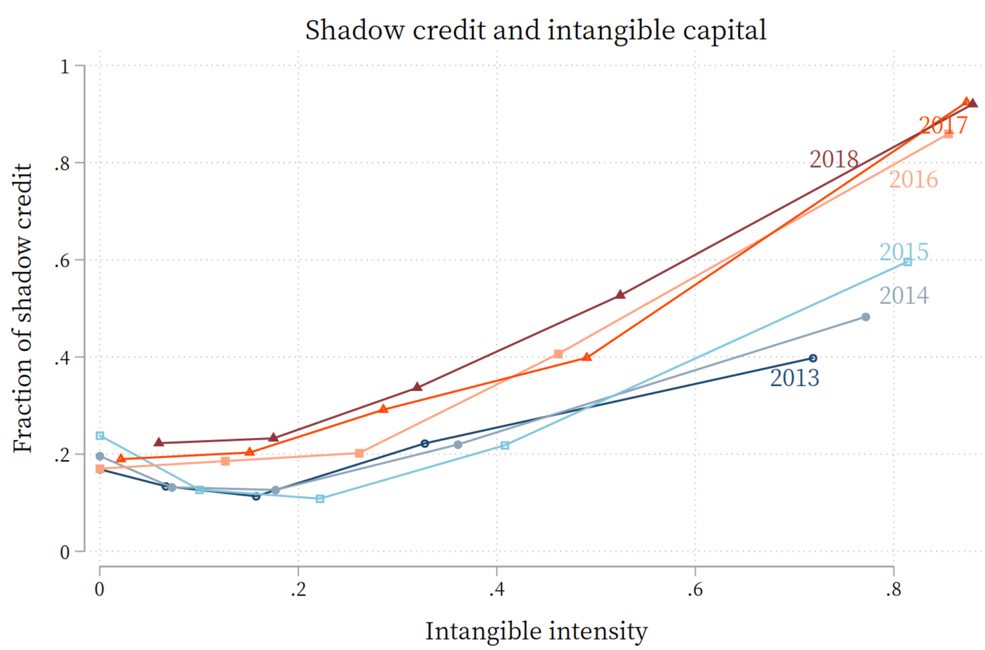
Industry (1-digit)	Frac	Cum.Frac
1st. Quintile		
Manufacturing	0.806	0.806
Transportation and storage	0.046	0.852
Wholesale and retail trade	0.037	0.889
Information and communication	0.032	0.921
Electricity, gas, steam and air conditioning supply	0.029	0.950
3rd. Quintile		
Manufacturing	0.801	0.801
Wholesale and retail trade	0.078	0.879
Information and communication	0.057	0.936
Professional, scientific and technical activities	0.038	0.974
Arts, sports and recreation related services	0.006	0.980
5th. Quintile		
Manufacturing	0.404	0.404
Information and communication	0.358	0.762
Wholesale and retail trade	0.140	0.902
Professional, scientific and technical activities	0.045	0.948
Business facilities management and business support services	0.025	0.972

Table 7: Top 5 detailed industries by intangible intensity quintiles

Industry (5-digit)	Frac	Cum.Frac
1st. Quintile		
C30399 Manufacture of Other Parts and Accessories for Motor Vehicles n. e. c.	0.057	0.057
C26221 Manufacture of Printed Circuit Boards	0.030	0.086
D35200 Manufacture of Gas, Distribution of Gaseous Fuel Through Mains	0.023	0.109
C17210 Manufacture of Corrugated Cardboard and Cardboard Boxes	0.022	0.132
C24132 Manufacture of Pipes and Tubes, of Non-cast Iron or Steel	0.022	0.154
3rd. Quintile		
C26299 Manufacture of Other Electronic Valves, Tubes and Electronic Components n.e.c.	0.042	0.042
C30399 Manufacture of Other Parts and Accessories for Motor Vehicles n. e. c.	0.035	0.077
C21210 Manufacture of Finished Medicaments	0.029	0.106
C29271 Manufacture of Semiconductor- Manufacturing Machinery	0.025	0.131
C10800 Manufacture of Livestock Feeds and Prepared Animal Feeds	0.020	0.151
5th. Quintile		
J58222 Application Software Development and Supply	0.098	0.098
C21210 Manufacture of Finished Medicaments	0.078	0.176
J58211 Online and Mobile Game Software Development and Supply	0.050	0.226
J58221 System Software Development and Supply	0.047	0.273
C26429 Manufacture of Other Wireless Telecommunication Apparatuses	0.030	0.303



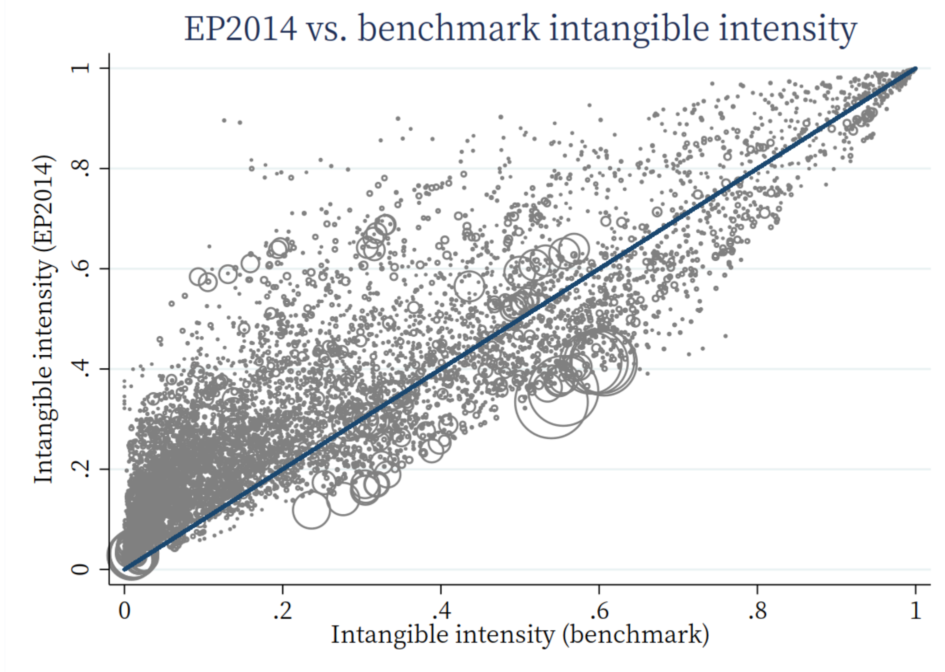
(a) Alternative to benchmark intangible intensity



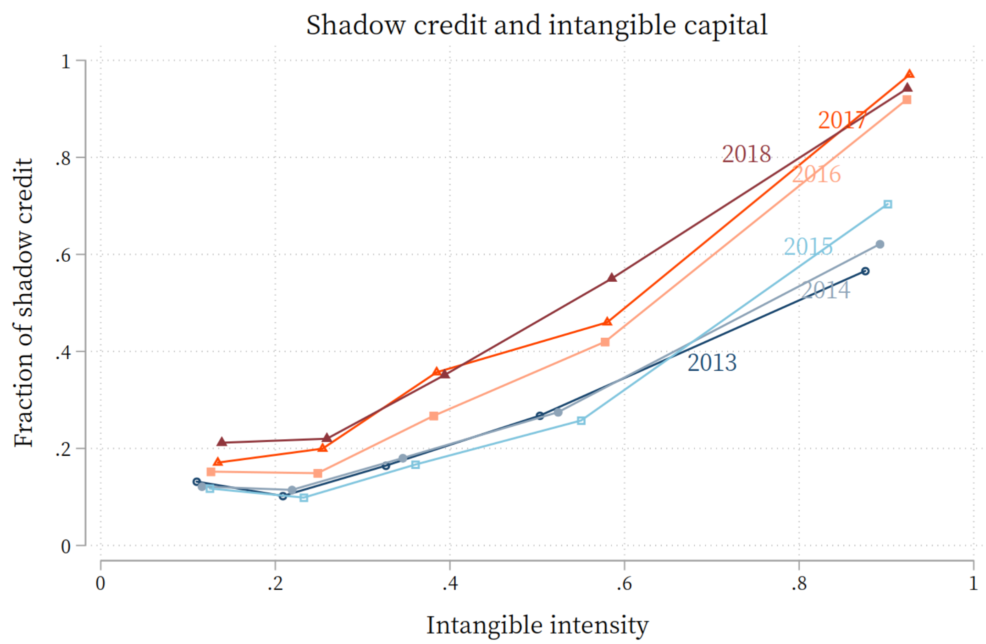
(b) Fraction of shadow credit by intangible intensity

Figure 12: Falato et al. 2020 to benchmark intangible intensity

Note: Blue diagonal line is a 45 degree line. All observations are weighted by the log total capital, which is the sum of tangible and intangible assets.



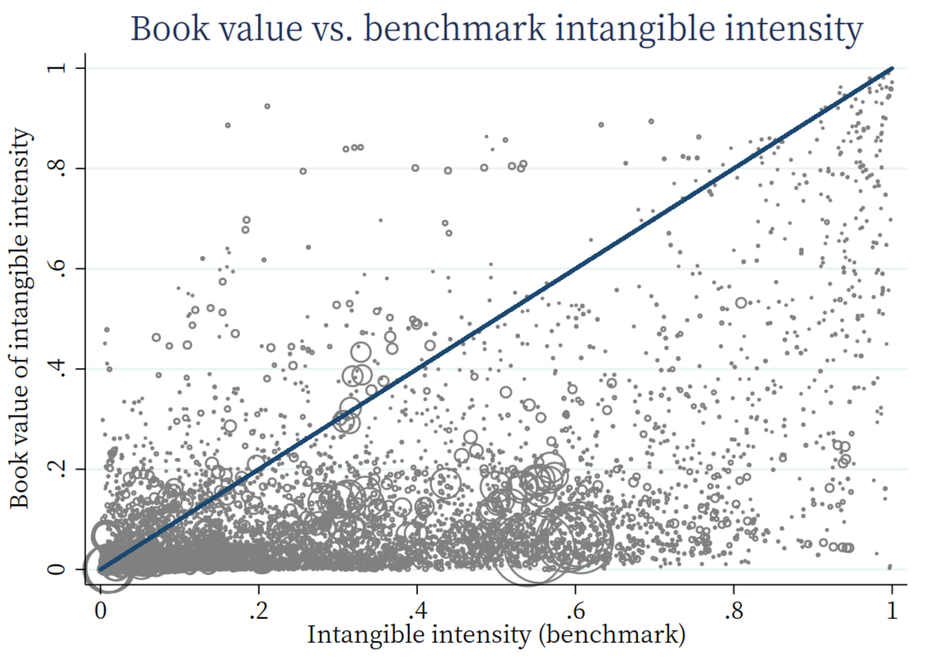
(a) Alternative to benchmark intangible intensity



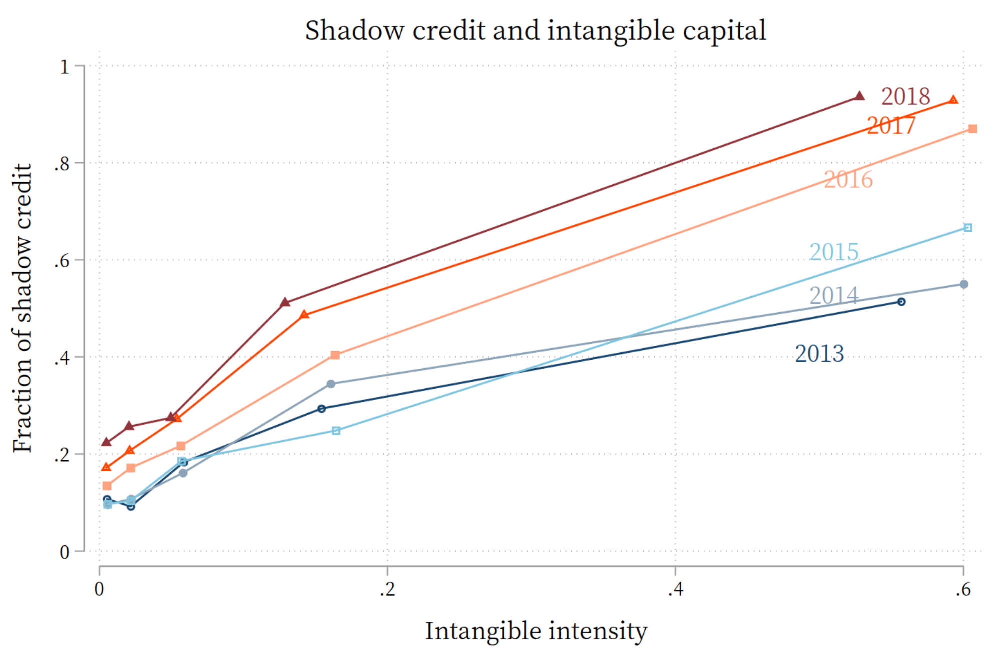
(b) Fraction of shadow credit by intangible intensity

Figure 13: Alternative intangible intensity measurement - Eisfeldt and Papanikolaou 2014

Note: Blue diagonal line is a 45 degree line. All observations are weighted by the log total capital, which is the sum of tangible and intangible assets.



(a) Alternative to benchmark intangible intensity



(b) Fraction of shadow credit by intangible intensity

Figure 14: Book value to benchmark intangible intensity

Note: Blue diagonal line is a 45 degree line. All observations are weighted by the log total capital, which is the sum of tangible and intangible assets.

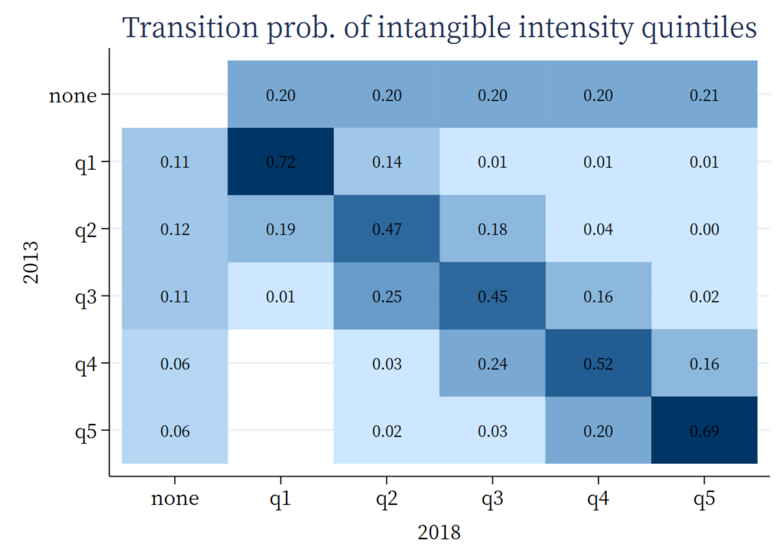


Figure 15: Transition probability of intangible intensity quintiles

B Productivity

We measure TFP by adopting the Generalized Method of Moments (GMM) framework proposed by Wooldridge (2009). We assume a Cobb-Douglas production function with total capital and labor:

$$Y_{it} = TFP_{it} L_{it}^{\beta_l} X_{it}^{\beta_x} \tag{18}$$

where X_{it} is the total capital:

$$X_{it} = intan.K_{it} + tan.K_{it} \tag{19}$$

Data We take the following variables from KisValue, from years 2010 to 2019, annual measures:

- sales : SALES(NET)[121000]
- cost_of_sales : COST OF SALES[122000]
- wage_bills : Personnel expenses[124100]
- tang_assets : TOTAL TANGIBLE ASSETS[113200]

Since some firms are delisted from one stock exchange and newly listed in another, we manually track those cases and merge into a single time series for each firm. For mergers and acquisitions, we record breaks in the time series manually.

C Interest rates

In this section, we investigate existing data for the interest rates on loans and bonds. Since our credit data does not include any information on interest rates, we collect data from various sources in order to illustrate interest rates by the types of borrowing (loans/bonds) and borrower characteristics.

Data There are two main sources for the interest rate data. First, we use the data from Bank of Korea to analyze the distributions of bank loan interest rates extended to large firms at an aggregate level.[25] We also use average yields on AA- and BBB- rated corporate

[25] Table 1.3.3.3. Shares of Deposits and Loans By Interest Rates Level (Newly Extended), Loans to Large Corporations(Total), Economic Statistics System, Bank of Korea. While the data of interest rate of loans extended to small and medium sized enterprises is also available, given that a majority of public firms counts as large firms, we focus on the large corporation data in this paper.

bonds (O.T.C), as well as average interest rates on corporations by three types of non-bank financial institutions (Mutual Savings Banks, Mutual Credits, and Trust Accounts).[26]

The second source of data is the firm balance sheets, where we infer "effective interest rates" by calculating total amount of interest payments over the outstanding amount of borrowing. We can calculate two types of interest rate based on the balance sheet information, namely loans and bonds. We use KisValue data, which is the main firm balance sheet data source of this paper. Names of the variables used to construct effective interest rates are the following:

- effective interest rate on loans = (Interest expenses[126110]) ÷ (Short-term borrowings[115130] + Current portion of long-term borrowings[115191] + Current portion of LT borrowings in foreign currency[115192] + Long-term borrowings[116200])
- effective interest rate on bonds = (Interest on bonds[126120]) ÷ (Total short-term bond[115400] + Current portion of bonds[115193] + Total bonds[116050])

Based on the calculated effective interest rates, we also investigate within-firm "bond premiums", which are the effective bond rates net of loan rates.

Aggregate interest rates The Bank of Korea interest rate distributions are aggregated based on administrative data of loan rates extended by commercial and special banks to large corporations. Figure 16 summarizes the loan interest rate distributions for months December 2013 and December 2018.

In comparison to bond yields, bank loan interest rates are in between the two bond ratings, AA- and BBB-, but closer to the AA- than BBB- on aggregate. Left panel of Figure 17 describes the timeline of bank loan interest rates by corporate size and bond yields by ratings. While the bank loan premium compared to AA- yield varies over time, interest rates on loans are consistently higher than AA- and lower than BBB- for all time periods, regardless of the size of corporations.

Finally, for a subset of non-bank lenders, the Bank of Korea provides interest rates for corporate loans. On the right panel of Figure 17, three non-bank lenders' interest rates are depicted, in addition to the bank loan rates for large corporations and bond yields of BBB-

[26] 1.3.2.2. Market Interest Rates(Monthly), Yields on Corporate Bonds: O.T.C (3-year, AA-, BBB-), 1.3.4.2. Interest Rates on Loans and Discounts: MSB-Loans To Corporations, Mutual Credits - Loans to Corporations, Trust Accounts Loans To Corporations.

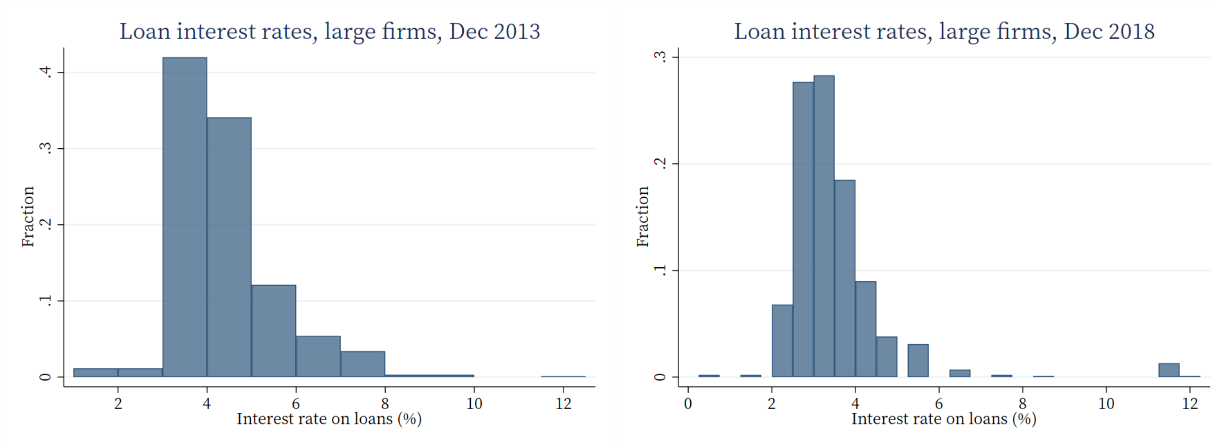


Figure 16: Interest rates to large corporations by banks, December 2013 and 2018

Note: Interest rate distributions are top- and bottom-coded. The lowest brackets for the interest rates are *3 percent and below* in 2013, and *2 percent and below* in 2018. The top bracket is *12 percent and above* in all years. Banks include both commercial and special banks.

ratings for comparison. These aggregate rates vary in the range from bank loan rates for large corporations to BBB- bond yields, with Mutual savings offering the highest interest rates on average compared to Trust accounts and Mutual credits showing lower rates on average.

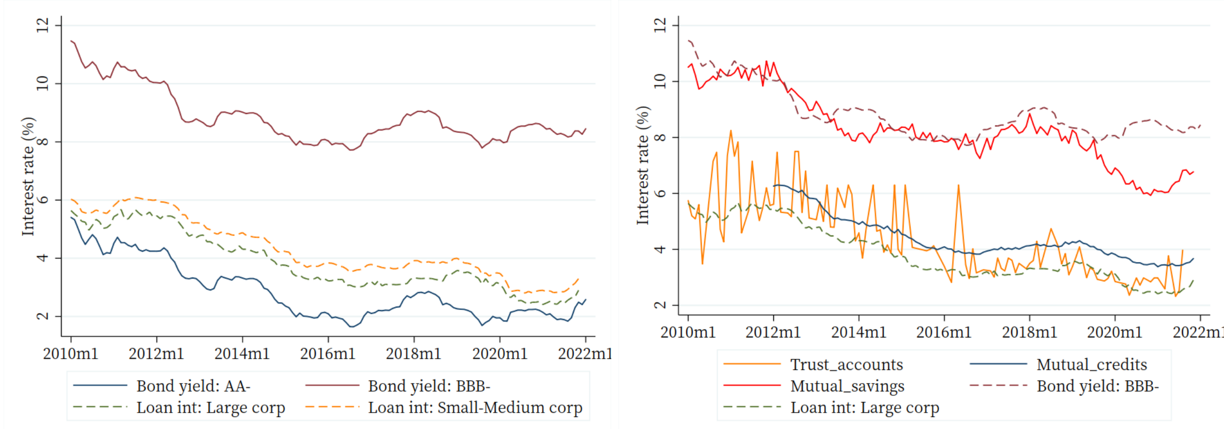


Figure 17: Interest rates to corporations by types of borrowing

Note: Interest rates by non-banks are available only at a general corporation level.

Effective interest rates at firm level Figure 18 summarizes distributions of the effective interest rates and bond premiums for the beginning (2013) and the end (2018) of the sample period. In 2013, interest rates for both loans and bonds show similar distributions, with a median bond premium of 0.058%. However, at the end of the sample period, we observe that interest rates on bonds are on average higher than those on loans, with a median of 1.89% bond premium. Compared to the Bank of Korea aggregates, we confirm that our firm-level bank loan rate distribution is similar to the administrative data.

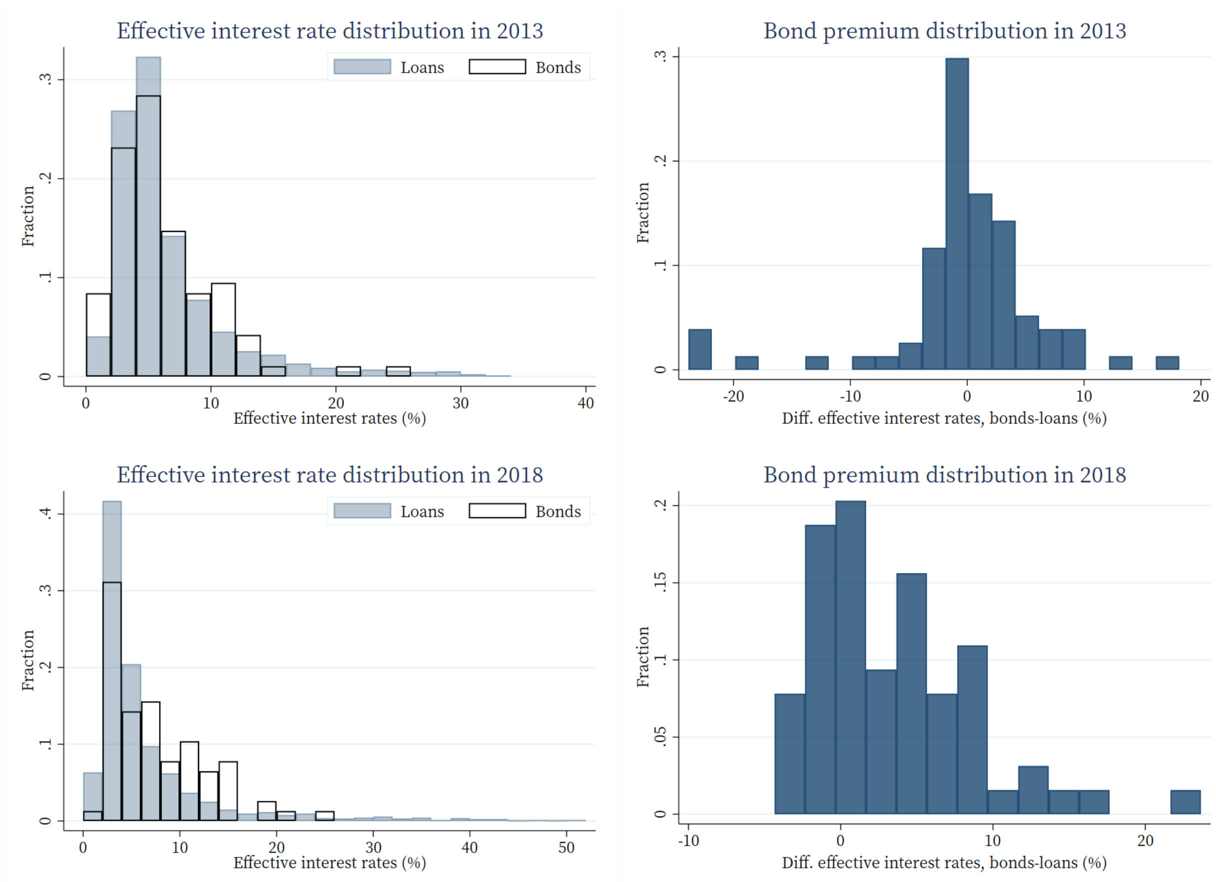


Figure 18: Effective interest rates and bond premium distribution, 2013 and 2018

Note: Top and bottom 5% of the values are windsorized.

D Additional figures and tables

Table 8: Summary statistics: annual data

Variable	Obs	Mean	Std. Dev.	Min	Max
Credit data					
Log real bank credit	8379	22.819	2.281	13.769	30.172
Log real shadow credit	10191	20.825	2.622	13.769	30.021
Frac. shadow to total credit	10400	.416	.395	0	1
Balance sheet data					
Log TFP	9588	-.481	.807	-10.687	3.156
Intangible intensity	9363	.327	.287	0	1
Log real intangible capital	9443	22.934	1.757	12.02	32.001
Log real total capital	10376	24.384	1.892	12.02	32.618
Log real tangible assets	10283	23.86	2.173	10.873	31.844
Log real net sales	10269	25.224	1.71	14.873	32.736
No. listed years	10400	12.855	11.356	0	62

Note: The data is annual and at a firm level from 2013 to 2018. The credit data based on the firm-lender matched accounts, aggregated at a firm level by the bank and shadow bank groups. The original data is at quarterly frequency, and we use the 4th quarter of each year. The balance sheet data is sourced from KisValue. All variables are reported in real Korean Won (KRW) using a GDP deflator from the Bank of Korea with 2015 as base year. The number of listed years is calculated as the current fiscal year minus the listed year.

Table 9: Intangible intensity, productivity, and firm size

	(1)	(2)	(3)
VARIABLES	intang.intensity	intang.intensity	intang.intensity
$\ln TFP$	0.0338***	0.0254***	0.000999
	(0.00707)	(0.00625)	(0.00257)
$\ln Emp$	-0.0414***	-0.0196***	-0.0444***
	(0.00510)	(0.00467)	(0.0101)
Observations	8,733	8,687	8,618
Fixed effects	Year	Yr*Ind	Yr*Ind, Firm
R2	0.0428	0.390	0.948

Note: All standard errors (in parentheses) are clustered at the firm level. *** p<0.01

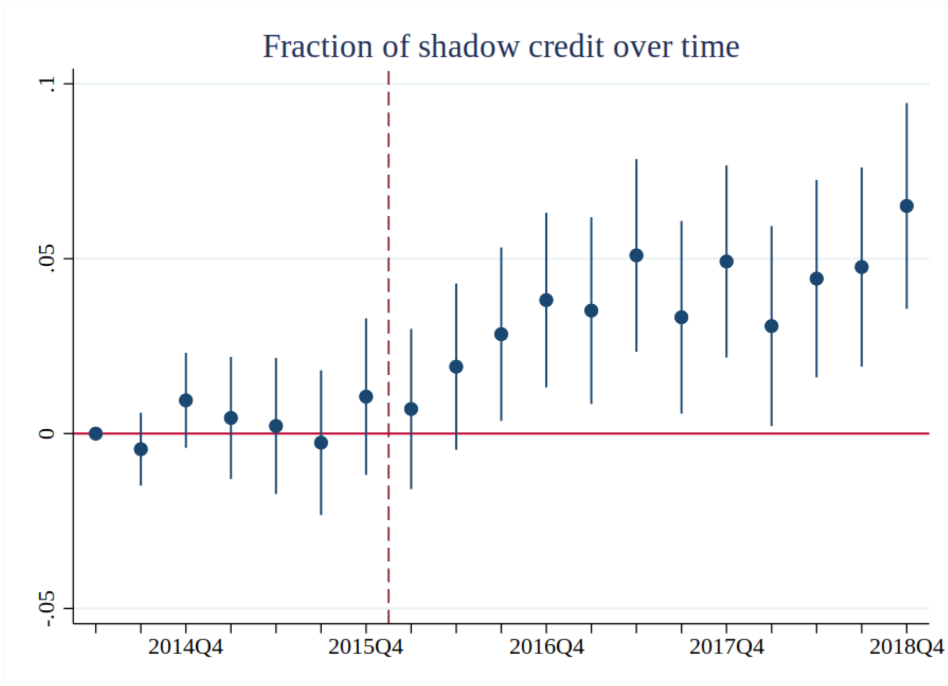


Figure 19: Changes in the fraction of shadow credit over time

Note: The initial sample period (2014Q2) is set as baseline. Standard errors are clustered at the firm level.

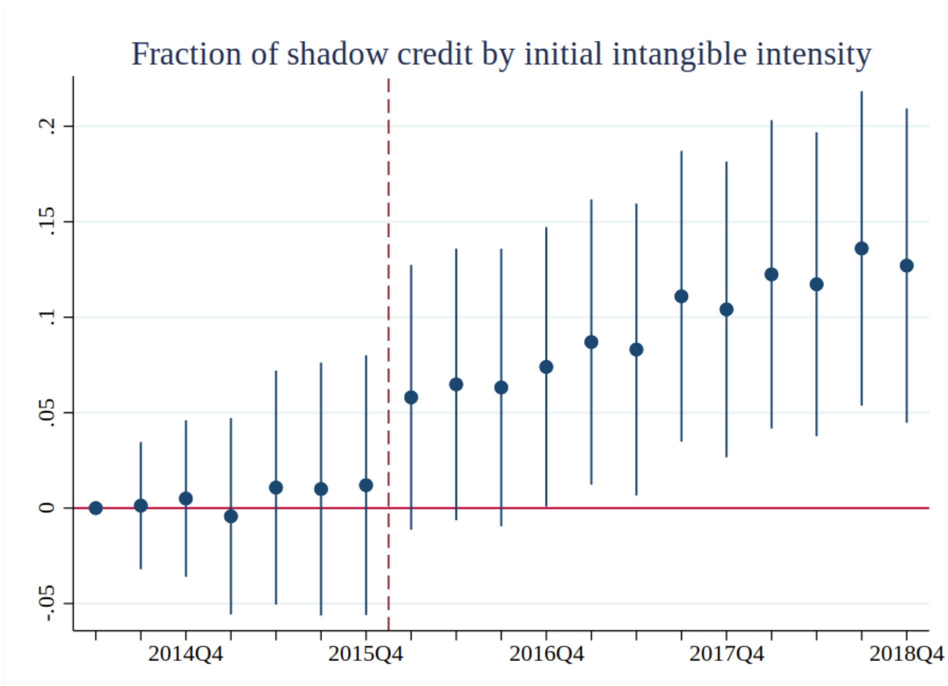


Figure 20: Changes in the fraction of shadow credit by initial intangible intensity ratio

Note: The initial sample period (2013Q2) is set as baseline. Standard errors are clustered at the firm level.

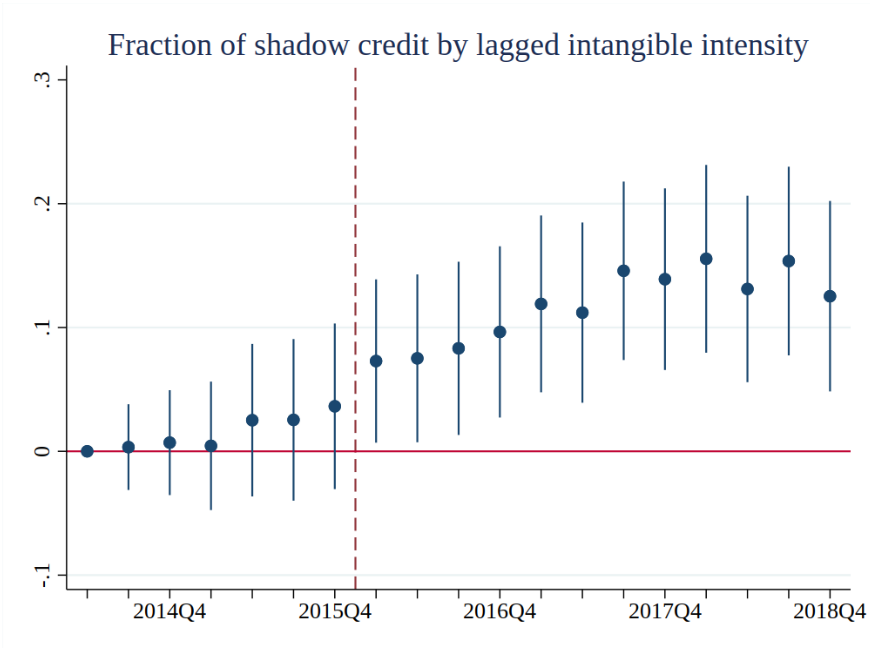


Figure 21: Changes in the fraction of shadow credit by lagged intangible intensity ratio, without controlling for TFP

Note: The initial sample period (2013Q2) is set as baseline. Standard errors are clustered at the firm level.

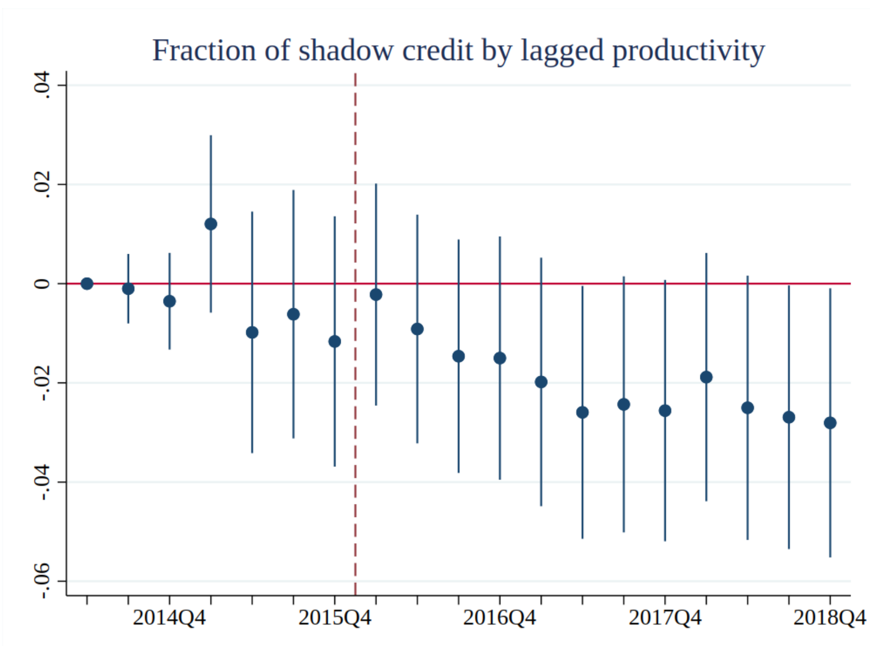


Figure 22: Changes in the fraction of shadow credit by lagged productivity

Note: The initial sample period (2013Q2) is set as baseline. Standard errors are clustered at the firm level.

E Model appendix

E.1 Proofs

Lemma 1 Recall the definition of capital ratio $CR = \frac{\sum \ell_i - D}{\sum \ell_i \omega_i}$. Under a positive capital requirement (CR>0), an increased investment in asset ℓ_j can only partially be financed with higher deposits D. To find by how much, we use the implicit function theorem

$$\frac{\mathrm{d}D}{\mathrm{d}\ell_j} = -\frac{\partial CR/\partial \ell_j}{\partial CR/\partial D} = -\frac{\left(\frac{\sum \ell_i \omega_i - \omega_j (\sum \ell_i - D)}{(\sum \ell_i \omega_i)^2}\right)}{\left(-\frac{1}{\sum \ell_i \omega_i}\right)} = 1 - \omega_j CR$$

This portion of the investment can be financed with deposits at the marginal rate of r^*, while the remaining portion must be financed with bank's own equity at the rate of r^{**}. Hence, the effective interest rate is

$$r_\ell = (1 - \omega_j CR) r^* + \omega_j CR r^{**}$$

■

Lemma 2 Consider the model described by formulas (5)-(10) with no impact of tangible assets on debt prices. The first-order conditions for the optimal choice of the two types of capital are:

$$k : -p_k + \frac{1}{1+r^*} \mathbb{E}\left\{ \alpha \xi z x^{\alpha-1} \frac{\partial x}{\partial k} \right\} = 0$$
$$n : -\varphi p_n n^{\varphi - 1} + \frac{1}{1+r^*} \mathbb{E}\left\{ \alpha \xi z x^{\alpha-1} \frac{\partial x}{\partial n} \right\} = 0$$

Combining these two formulas yields the marginal rate of substitution between the two types of capital:

$$k = \left(\varphi \frac{p_n}{p_k} \frac{1-\psi}{\psi} \right)^{\frac{1}{1-\nu}} n^{\frac{\varphi - \nu}{1-\nu}}$$

Taking the derivative of k with respect to n and setting it negative yields the ultimate condition:

$$\frac{\partial k}{\partial n} = \frac{\varphi - \nu}{1 - \nu} \left(\varphi \frac{p_n}{p_k} \frac{1-\psi}{\psi} \right)^{\frac{1}{1-\nu}} n^{\frac{\varphi - 1}{1-\nu}} < 0 \iff \varphi < \nu$$

■

E.2 Basel Risk Weights

In this section, we describe how risk weights are derived under the Basel system. We follow the main formula to calculate the risk weights directly in our model, and we introduce an interpolation method to obtain risk weights for any level of collateral.

At the core of the risk weight derivation lies the concept of *Loss Given Default* (LGD). This value implies the amount of haircut a lender should expect in the event of a default. We derive the LGD for any bank loan based on the recovery value of tangible assets, and assume that the relationship between the two follows a logistic function.

$$LGD = \frac{1}{1 + exp\left(\eta \left[\frac{(1-\lambda)kp_k}{\ell} - \iota\right]\right)} \tag{20}$$

Equation (20) implies that LGD is 100% for an unsecured loan and 0% for a fully secured loan. It follows a logit function for intermediate values of the collateral as fraction of the loan amount with a smoothing parameter of η and an inflection point at ι. In our application, we assume $\eta = 5$ and ι close to 0.5 (the latter is calibrated jointly in a moments-matching exercise).

Based on a particular value of Loss Given Default, and for a specific probability of default (PD) which is known precisely in our model, the risk weight ω under the Basel system is calculated as follows

$$\begin{aligned}
\omega = 12.5LGD &\Big[\Phi\Big(\frac{\Phi^{-1}(PD)}{\sqrt{1-corr}} + \frac{\sqrt{corr}}{1-corr}\Big)\Phi^{-1}(0.999) - PD\Big] \times mat_adj \\
corr =&0.24 - 0.12\frac{1-e^{-50PD}}{1-e^{-50}} \\
mat_adj =&\frac{1 + (maturity - 2.5) \times \Big(0.11852 - 0.05478\, log(PD)\Big)^2}{1 - 1.5 \times \Big(0.11852 - 0.05478\, log(PD)\Big)^2}
\end{aligned}$$

Intuitively, the above formula uses the Merton (1974) model where the borrowers default if their asset value drops below the due amount. The distribution of such losses can be assumed to be normal. However, when multiple assets' default realization is interdependent (for example due to a systemic risk factor) then the distribution of aggregate portfolio losses features a fat tail. Hence, the Basel formula follows Vasicek (2002) to include a correlation adjustment, as well as an adjustment for the maturity profile of cash flows.

E.3 Additional model figures

In this section, we provide the plots of policy functions for the two additional reform scenarios summarized in Table 5. First, Figure 23 plots the policy functions in the reform scenario where the cost of searching for a more favorable non-bank credit supply is elevated to prevent any rise in this type of financing. Indeed, as the bottom row shows, the borrowing decisions stay mostly unchanged relative to the pre-reform world in considerable contrast to the baseline Basel III reform scenario. As a result, in terms of the investment decisions we actually observe a modest substitution towards tangible capital and away from intangible assets which results in a decline in intangible intensity across the productivity distribution. This leads to a predicted 2% decline in aggregate output as evident in Table 5.

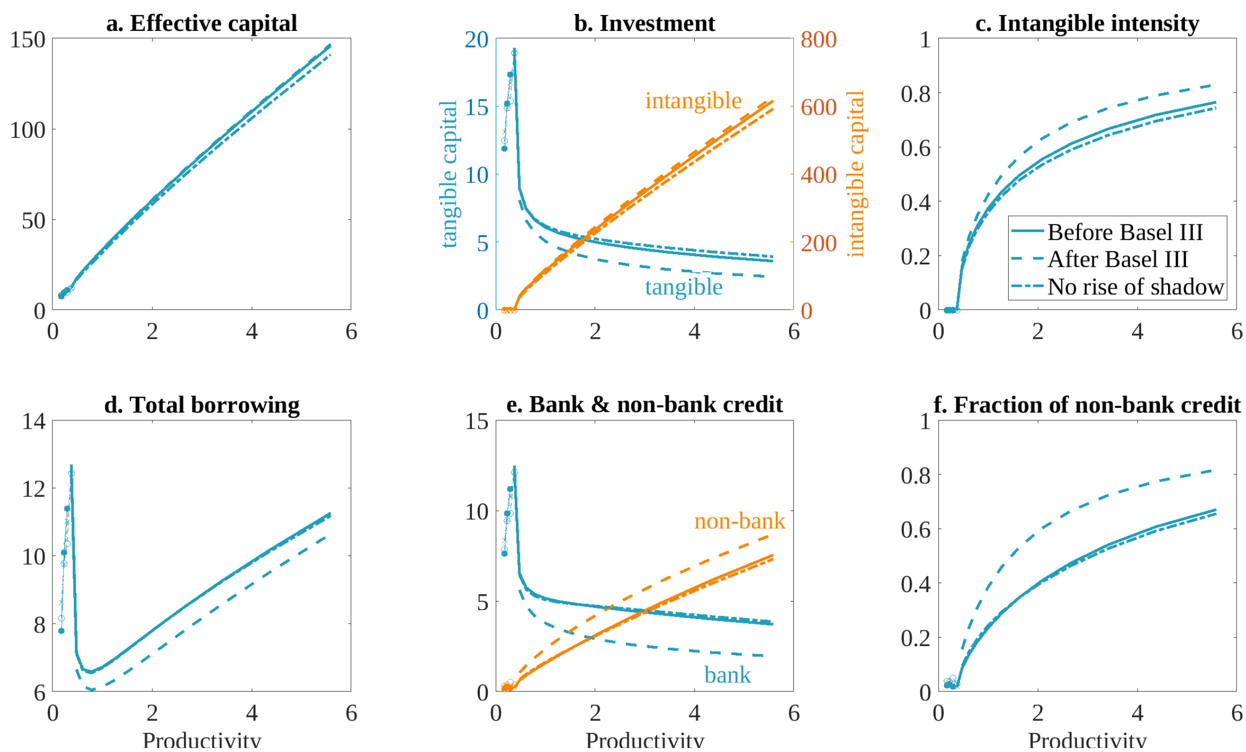


Figure 23: Model solution: "after Basel III" (CR=11.5%) + no rise of shadow

Note: The plots depict functions of initial temporary productivity z_0 for a fixed permanent type. Solid thick lines represent policy functions of firms who choose an interior solution for intangible assets ($n > 0$). Markers connected by thin lines represent policy functions of firms who choose a corner solution ($n = 0$).

Figure 24 plots the policy functions for the reform scenario where some of the intangible assets can also be used as collateral in borrowing. We observe significant changes, with the slope of both total borrowing and the effective installed capital increasing. All firms invest considerably less in tangible capital and considerably more in intangible assets, and the overall intangible intensity schedule shifts upwards. Interestingly, the slope of bank borrowing also changes sign with more productive firms now borrowing from banks more and as a result their fraction of shadow credit going down. This is not the case, however, for firms with average and low productivities. They borrow from banks less than in the baseline reform scenario, and about the same amount from shadow banks, and consequently their fraction of shadow credit goes up. The overall profile of the fraction of non-bank credit is now non-monotonic in productivity.

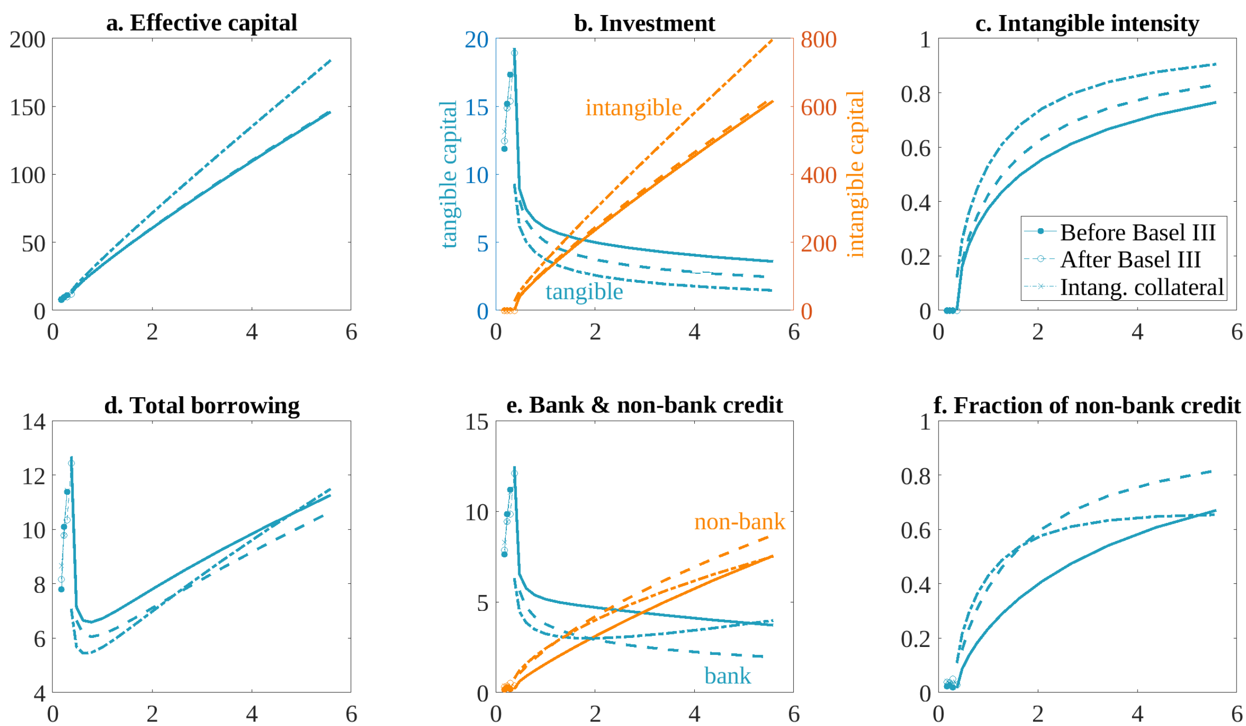


Figure 24: Model solution: "after Basel III" (CR=11.5%) + collateralizable intangibles

Note: The plots depict functions of initial temporary productivity z_0 for a fixed permanent type. Solid thick lines represent policy functions of firms who choose an interior solution for intangible assets ($n > 0$). Markers connected by thin lines represent policy functions of firms who choose a corner solution ($n = 0$).