Intangible Capital and Shadow Financing

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Abstract

This paper studies the nature of financial frictions that firms face in an increasingly intangible economy. Using new microdata from South Korea, we document that intangible-intensive firms disproportionately borrow from non-bank lenders. This heterogeneity in the mode of financing is magnified and leads to differential outcomes in response to an exogenous tightening of bank credit supply. We find that intangible-intensive firms are mostly unaffected, while traditional firms struggle to finance their growth. To explain these findings, we build a model of heterogeneous firms and two sources of financing: shadow and regulated bank, with collateral constraints for the latter. Higher collateral requirement drives intangible-intensive firms away from bank borrowing and results in the rise of shadow credit. A counterfactual experiment using the model shows that suppressing the rise of shadow financing comes at significant costs.

Keywords: Firm dynamics, shadow finance, intangible capital

JEL Classification Numbers: E44, E50, G21

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1 Introduction

The role of intangible capital has been rising steadily in the modern economy. By some accounts, investments in intangible assets increased by about 50% in the last two decades (Branstetter and Sichel, 2017), while their overall stock roughly doubled (Crouzet and Eberly, 2019). Because intangibles cannot be easily used as collateral, this trend has raised concern about the firms' ability to finance investments in the modern economy (Haskel and Westlake, 2018). At the same time, the landscape of financial intermediation has been increasingly shifting towards non-bank lenders, away from traditional banks (Lee, Lee and Paluszynski, 2022). Less onerous regulation, combined with recent technological advances in the area of fintech, has made non-bank lenders a preferred source of credit for many firms. In this paper, we show that these two trends are inherently related and ask: how do firms finance production and growth in the modern economy?

We use a new dataset of matched firm-lender credit accounts from South Korea, which includes an exogenous credit tightening event, to study the nature of financial frictions that firms face in an increasingly intangible economy. We first document that firms with higher intensity in intangible capital tend to borrow more from shadow lenders. Specifically, we measure the firm-level intangible capital using income statement data on expenses related to intangible investments such as research and development costs. Based on this, we construct an *intangible intensity ratio*, which is the share of intangible capital in firms' total capital. Using our data, we show that in 2013 firms in the top quintile of intangible intensity borrowed around 52% of their total credit from shadow lenders, compared to 13% for firms in the bottom intangible intensity 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. In 2018, at the end of our sample period, the fraction of shadow credit for firms in the top and bottom intangible intensity quintiles reached 92% and 22%, respectively. Over the years, all firms have borrowed more from shadow lenders, but those with high intangible intensity experienced disproportionate increases in their dependence on shadow credit.

To formalize the link between intangible intensity and shadow financing, we conduct an empirical analysis where we estimate the association of shadow financing with intangible intensity while controlling for productivity and total capital size. Using a set of regressions with firm fixed effects, we find that the *fraction of shadow credit*, which is defined as the amount of shadow credit over the sum of shadow and regulated bank credit, increases with intangible intensity and total factor productivity, while it decreases with the total capital size. Importantly, this relationship gets stronger in the aftermath of the banking reform. To understand why, we zoom in on individual firm-lender credit accounts and regress the changes in the quantity of credit, separately for banks and non-banks, against time dummies interacted with intangible intensity levels while controlling for firm and lender fixed effects. We find that the reform caused a statistically significant decline in bank borrowing for traditional, tangible-intensive firms, while it had no impact on the most intangible-intensive firms. Moreover, the reform does not have any effect on the former's borrowing from shadow lenders, while it causes the latter to significantly increase their non-bank financing. This suggests that, contrary to conventional wisdom, it is the firms with mostly tangible assets who suffer from a bank tightening episode, while intangible-intensive firms appear to be mostly unaffected, or even to benefit from it.

As a final piece of the empirical analysis, we investigate the effects of the reliance on shadow financing on the firms' real outcomes. First, we find that prior to the reform, a higher fraction of shadow credit is associated with lower growth of output and lower investment rates. This is intuitive given that financing a productive process with collateralized loans is easier and less expensive than with bond issuance. However, an interaction term of shadow financing with the post-reform dummy variable has the opposite sign and mostly offsets this natural advantage of regulated bank credit. For example, after the reform, higher reliance on shadow financing is essentially unrelated with the rates of investment in total capital, and it is associated with higher investment in tangible assets. This result, combined with our previous findings on the effects of the reform period on firm's credit growth, paints a clear story. Traditional, tangible-intensive firms lose access to bank credit and struggle to finance their growth with non-bank financing. On the other hand, intangible-intensive firms are mostly unaffected by the bank tightening event and actually benefit from the expansion of the shadow lending sector by growing faster.

To understand these findings, and to measure the impact of credit tightening on the macroeconomy, we build a dynamic quantitative model of heterogeneous firms who seek to finance their capital investments with corporate credit. Capital consists of tangible and intangible assets, and firms are heterogeneous in the intangible-intensity of their production (which is exogenously assigned to them and varies slowly over time). In order to borrow from regulated banks, firms must post collateral in the form of physical capital. Alternatively, they can turn to shadow banks to obtain unsecured credit with much higher limits, but at a higher interest rate. Due to the nature of the collateral constraint, in the stationary distribution of the model, it is the least wealthy, the most productive, and the most intangible-intensive firms who obtain the largest share of their loans from shadow banks. These model results corroborate our main observations from the data.

We then calibrate the model to the Korean corporate sector in years 2010-2013, and use it to conduct three reform exercises. First, in our baseline exercise, we simulate a period of credit crunch by simultaneously restricting the credit supply from regulated banks and by tightening the collateral constraint. This exercise can be thought of as mimicking the period of Basel III implementation in South Korea (Lee, Lee and Paluszynski, 2022). We find that, consistent with our empirical findings, the fraction of shadow credit increases, and overall leverage drops significantly in the new stationary distribution, especially so for highly intangible-intensive firms.

Second, we conduct a counterfactual experiment in which, together with the tightening of the collateral constraint, we also increase the interest rate on shadow loans. This exercise simulates a potential government intervention aimed at making shadow credit less accessible to borrowers. We find that in such a counterfactual scenario the increase in the fraction of firms borrowing from shadow banks is prevented, but this comes at the expense of a further reduction of physical capital and output in the economy (beyond the one induced by tighter lending standards).

Third, we examine another counterfactual scenario where, due to a change in the legal framework or institutional settings, all capital can be pledged as collateral, including intangible assets. In this case, firms reduce their reliance on shadow financing but not by much relative to the pre-reform economy due to the credit tightening event. However, such a change is accompanied by an increase in output, capital and wealth.

To evaluate the effect of credit tightening on the broad macroeconomy, we calculate the transitions in all exercises, and measure the short-run effects induced by the reform. We find that output drops by up to 0.75% in the baseline scenario, and eventually converges to about 0.5% below the pre-reform equilibrium. Furthermore, in the counterfactual scenario in which the government goes after shadow lenders, the short-term decline in output exceeds 1.5% and eventually rebounds to about 0.75% below the pre-reform level. By contrast, in the second counterfactual that allows for all capital to be collateralized, output increases by up to 5% before converging in the long run to 0.2% above the pre-reform level. This analysis shows that any intervention aimed at increasing financial stability may come at a significant efficiency cost, especially in the short term. However, these costs can be offset (and, in fact, dwarfed) by promoting new institutional arrangements that would make collateralization of intellectual property feasible.

Literature review This paper builds on the literature of firm dynamics with financial frictions. The importance of collateral constraints in the aggregate economy has been extensively studied following a seminal paper by Kiyotaki and Moore (1997), and the literature of macro-finance has grown exponentially after the 2007-2009 Great Recession. Recent studies find that firm heterogeneity is important in understanding the effects of financial frictions on real outcomes such as employment and productivity growth (Levine and Warusawitharana, 2019, Siemer, 2019). Bassetto, Cagetti, and De Nardi (2015) also find that negative credit shocks have persistent effects on real activity. The latest wave of this research seeks to understand the role of various non-traditional sources of firm financing. Salomao and Varela (2021) show that more productive firms in emerging economies choose to borrow in foreign currencies while getting exposed to exchange rate risk. Faria e Castro, Paul and Sanchez (2021) develop a model of relationship lending that leads banks to offer loans at better terms ("evergreen" them) to firms with low productivity. Complementing these existing papers, we show that firms with high intangible capital intensity tend to rely on shadow financing, increasingly so in times of tightening financial frictions.

More specifically, this paper contributes to the emerging literature on the role of intangible capital in the economy. McGrattan (2020) and Crouzet and Eberly (2021) both argue that accounting for intangible assets is essential to understanding the recent trends in measured productivity growth. Sun and Xiaolan (2019) propose that employee contracts may feature a deferred compensation structure in order to incentive intangible investments. Li (2020) and Falato et al. (2020) point out that the exogenous shift towards intangible capital can lead to the observed corporate savings glut. Altomonte et al. (2020) claim that some of the observed dispersion in firms' markups are due to the frictions in financing intangible investments. In relation to these papers, we emphasize the increasing dependence of non-bank financial intermediation for intangible-intensive firms.

Our work is also related to the role of shadow (non-bank) financial intermediaries in the provision of credit to firms. The rise of shadow banks, or non-bank lenders, has been well documented in many angles including household debt (Jiang et al., 2020) and residential mortgage in the US (Buchak et al., 2018), in China in response to monetary policy (Chen, Ren, and Zha, 2018), and corporate lending in South Korea (Lee, Lee and Paluszynski, 2022), to just name a few. The literature has discovered that there are two main channels that potentially cause a rapid growth of non-bank sector: technological advance such as fintech (Buchak et al., 2018, Jagtiani and Lemieux, 2017) and regulatory arbitrage (Plantin, 2014). While most of the existing papers primarily focus on the changes in the credit supply side, we complement their studies by examining the demand side of non-bank credit.

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 introduces our econometric methodology and discusses the results. Section 4 introduces the quantitative model of heterogeneous firms and Section 5 presents the results. Section 6 concludes.

2 Background

2.1 Data description

There are two main datasets used in this paper. First 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 at annual frequency.[1] For the sample period of 2013-2018, we observe about 1900 firms on average, together with around 330 unique lenders each year, which gives us a total of 87,781 firm-lender-year observations. A unique advantage of this dataset is that lenders include not only commercial banks, but also non-banks such as insurance companies and wealth management companies. In the following, we refer to "bank" credit of a firm as the total sum of credit extended by commercial banks[2] and "shadow" credit as the total credit extended by all other lenders other than commercial banks.[3] One of the main variables constructed from this dataset is the *fraction of shadow credit*, which is the amount of shadow credit over the sum of bank

[1] The credit data is at quarterly frequency. However, in order to better link with the balance-sheet data, which is more complete at annual frequency, we focus on the 4th quarter data only for most of our analysis.

[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 lenders, encompassing a wide variety of financial institutions. The main reason why we focus on the distinction between commercial banks and shadow lenders is because a new set of banking regulations, namely Basel-III, were applied only to commercial banks during our sample period. As studied in more detail by Lee, Lee and Paluszynski (2022), this new regulation tightened credit supply by banks while shadow lenders grew in both size and significance due to the spillover effect.

and shadow credit for each firm and year level. In Appendix, we provide more detailed description of the data.

In order to study the firm characteristics in relation to the modes of financing, we link above credit data with a 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 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 position in order to estimate tangible as well as intangible assets and productivity at a firm level.

2.2 Construction of intangible capital and productivity

We measure intangibles and total factor productivity (TFP) based on the balance sheet data of each firm. In contrast to tangible assets, intangibles are often accounted as a stream of expenses, rather than a stock of assets. In measuring TFP, we first follow conventional method of using tangible assets only and compare the results with an alternative where both tangibles and intangibles are used. We elaborate on the construction of both intangibles and TFP, and discuss potential shortcomings of our measurement. More details of data collection can be also found in Appendix A.1 and B.1.

Intangible capital We construct intangible capital stocks based on the flow of expenses in Selling & General Administrative (SGA), which includes Research and Development Costs (R&D) as well as travel, training, promotion, and salaries. Following Eisfeldt and Papanikolaou (2014) and more recently Falato et al. (2020), we estimate *organization capital* using a fraction of SGA expenses and assuming perpetual inventory method. More specifically, we assume that 30% of SGA expenses are used as an "investment" for organization capital, and it depreciates by 20% annually. All expenses are deflated using a GDP deflator. Based on this estimation of intangible capital, we estimate intangible to total capital ratio (*intangible intensity*) by computing the ratio of intangibles over the sum of book value tangible assets and intangibles. The distributions of intangible intensity at the beginning and the end of our sample period, years 2013 and 2018, are described in Figure 16 in the Appendix. Intangible intensity distributions are bi-modal in all years: one group of firms have lower intangible intensity of around 0.2 to 0.3, while the other group has extremely high intangible intensity of nearly 1. Furthermore, the overall intangible intensity is increasing over the years. In the next section, we summarize firm characteristics such as size and productivity by intangible intensity in further detail.

While the above method of using SGA expenses is our benchmark measurement of intangible capital, we compare the results with other alternative measures in order to check the robustness. First, we use more detailed subcategories of SGA expenses in order to separately measure *knowledge capital* based on R&D expenses only (Falato et al., 2020) and exclude salaries from the organizational capital. More specifically, SGA expenses are the sum of Personnel, General administrative, Selling, and Other that include R&D. We build organization capital using the sum of General administrative and Selling expenses, and knowledge capital using the sum of Research costs, Ordinary R&D cost, and Ordinary development under the Other expenses category, following analogous approach as in the benchmark. Data for more detailed subcategories are less complete compared to the SGA, and we impute any missing expenses as 0. We find that the alternative measure of intangible intensity is highly correlated with the benchmark with a correlation coefficient of 96.5%, affirming our benchmark approach. In Figure 14 in the Appendix, we compare the two measures of intangible intensity in a scatter plot, visualizing their high correlations.

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 Figure 15 in Appendix shows. In a simple OLS, book value intangible intensity is around 55% of the benchmark measure. Nevertheless, regressions show that the two measures are positively and significantly correlated together.

Productivity In order to measure total factor productivity (TFP), we approach in two ways. First is the conventional method, by constructing capital stocks based on tangible assets. Second approach adds intangible capital to the stock of tangible capital, and use analogous method to the first approach. We find that the two measures result in TFPs that are highly correlated with the correlation coefficient of 96%. We choose the second approach as our benchmark measure of TFP, which makes it more consistent with the quantitative analysis following this section, but empirical results using the conventional method are reported in the Appendix B.2 as well.

In order to measure TFP including intangible capital, we closely follow the existing literature (Syverson, 2011) except that in place of physical capital we use the sum of tangible and intangible capital. We estimate a panel of log TFP series by first estimating 2-digit industry average of labor shares (α_L). We assume a constant returns to scale technology ($\alpha_K = 1 - \alpha_L$). Then, the log TFP of a firm is derived as a residual of log value added net of labor ($\alpha_L \times$log number of employee) and capital ($\alpha_K \times$ real tangible and intangible capital) expenditures. More details of constructing tangible capital stocks using perpetual inventory method and data source can be found in Appendix B.1.

2.3 Intangible capital and shadow financing in Korean data

We now describe the aggregate trends for intangible intensity and shadow financing using the Korean data. Figure 1 plots the two measures, based on all firms in our sample, over the time period of interest.[4] 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 a slight reversal in year 2018. What drives the rise in the fraction of shadow credit is simultaneously a decrease in the total amount of regulated bank loans and an increase in the amount of shadow credit (in Lee, Lee and Paluszynski (2022), we document these trends in more detail). As for the intangible intensity, both tan-

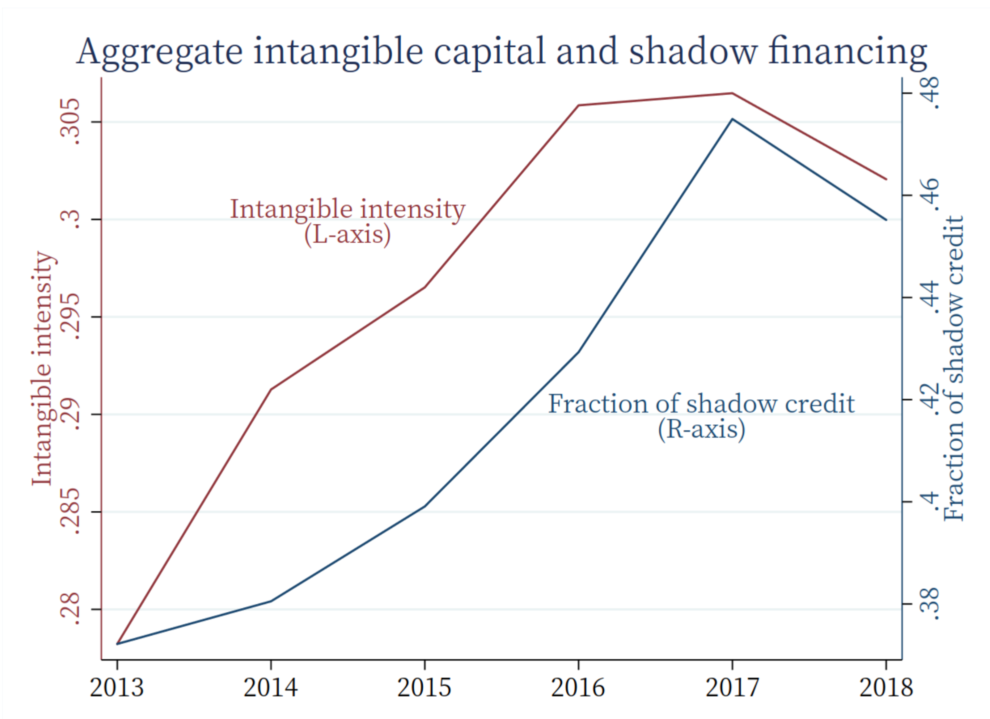


Figure 1: Aggregate intangible intensity and fraction of shadow credit

[4]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.

gible and intangible assets are growing in general but the speed of intangible asset growth is faster than that of tangible assets. The reversal of the shadow credit fraction at the end of sample period can be explained by a change in banking regulatory measures, which incentivize banks to extend more credit to corporate sector compared to households.[5] This coincides with a slower growth of intangible assets and tangibles in 2018.

2.4 Shadow financing by intangible intensity

The main motivating observation of this paper is that firms with more intangible capital as a fraction of the total capital tend to borrow more from shadow lenders. Moreover, this trend intensified over time, especially towards the end of the sample period. Figure 2 summarizes such observations. The bottom connected line (navy, 2013) plots the fraction of shadow credit, which is the amount of shadow credit to the total bank and shadow credit, against intangible intensity, which is the ratio of intangible capital to the sum of intangible and tangible capital.

In Figure 2, there are five dots for each line, representing median points in each quintile by intangible intensity. The graph shows that in 2013, for firms in the bottom 20% distribution of intangible intensity, a median firm has about 11% of capital as intangibles and borrow 13% of total credit from shadow lenders. For the firms in the top quintile, on the other hand, has much higher intangible intensity (90%) and borrow more than 50% of their credit from shadow lenders. In 2018, which is plotted in maroon color, firms in all quintiles have higher intangible intensity, as well as fraction of shadow credit. However, the increase in shadow credit fraction is not uniform across the firms: those with the highest intangible intensity experienced disproportionately sharp increases in the fraction of shadow credit. Moreover, the fraction of shadow credit particularly accelerated in year 2016, when a new set of banking regulation Basel III was implemented in Korea with legal penalty, as Figure 19 shows in the Appendix. This cross-sectional and time series observations of correlation between the intangible intensity and the fraction of shadow financing are key motivations of this paper. In the quantitative section of the paper (Section 5), we revisit the Figure 2 and test how much our model can explain such patterns of intangible intensity and shadow credit.

In order to better understand the changes in the fraction of shadow credit, we next in-

[5] In particular, banks in Korea are subject to loan-to-deposit ratio regulation. When calculating the ratio, each loan is assigned a "risk weight". In 2018, risk weights on corporate loans were reduced by 15%, whereas those on household loans were increased by 15%.

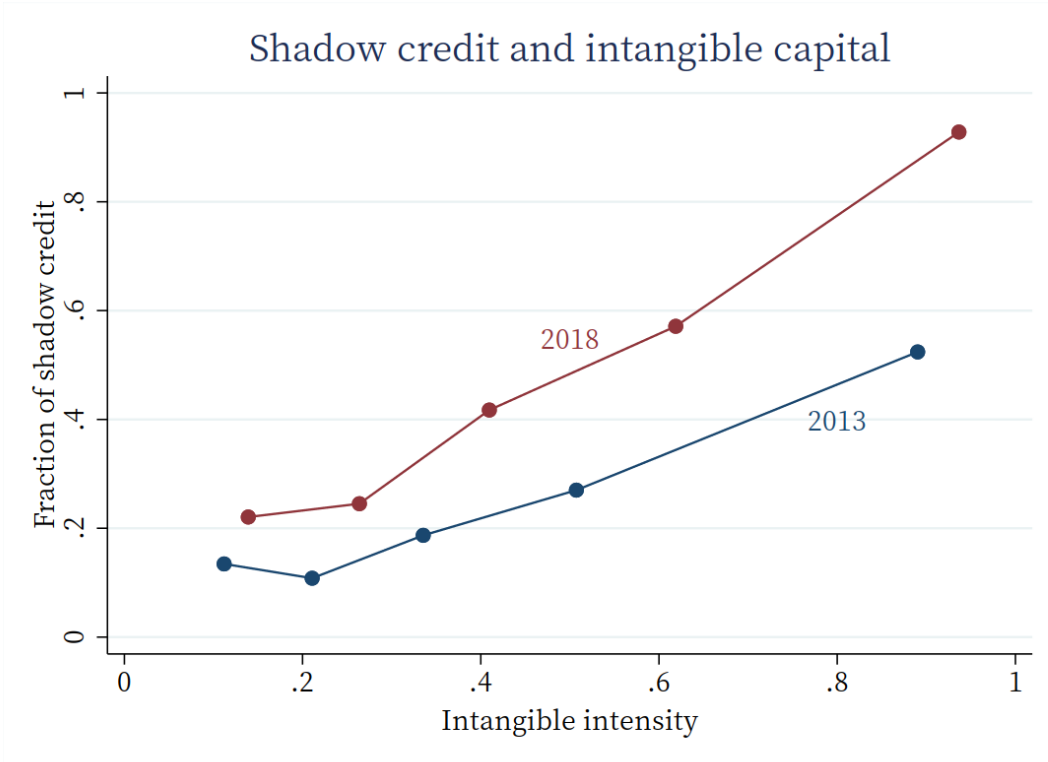


Figure 2: Fraction of shadow credit by intangible intensity

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

vestigate changes of shadow and bank credit relative to total capital, which includes both tangible and intangible assets. In Figure 3, we plot shadow credit to total capital ratio (navy bars) for each quintile of intangible intensity in 2013 and 2018. Bank credit to total capital ratios (blank bars) are plotted analogously. It shows that the overall increase in the fraction of shadow credit is a result of simultaneous increases in shadow credit and decreases in bank credit. Notice that the sum of shadow and bank credit to total capital ratio decreased across all quintiles, indicating that the amount of decrease in bank credit was larger than the increase in shadow credit. Furthermore, firms with the highest intangible intensity experienced pronounced increases in the shadow credit as well as sharp decreases in bank credit.

2.5 Interest rates paid by lending source

While our main credit accounts dataset contains only the quantities of credit, 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

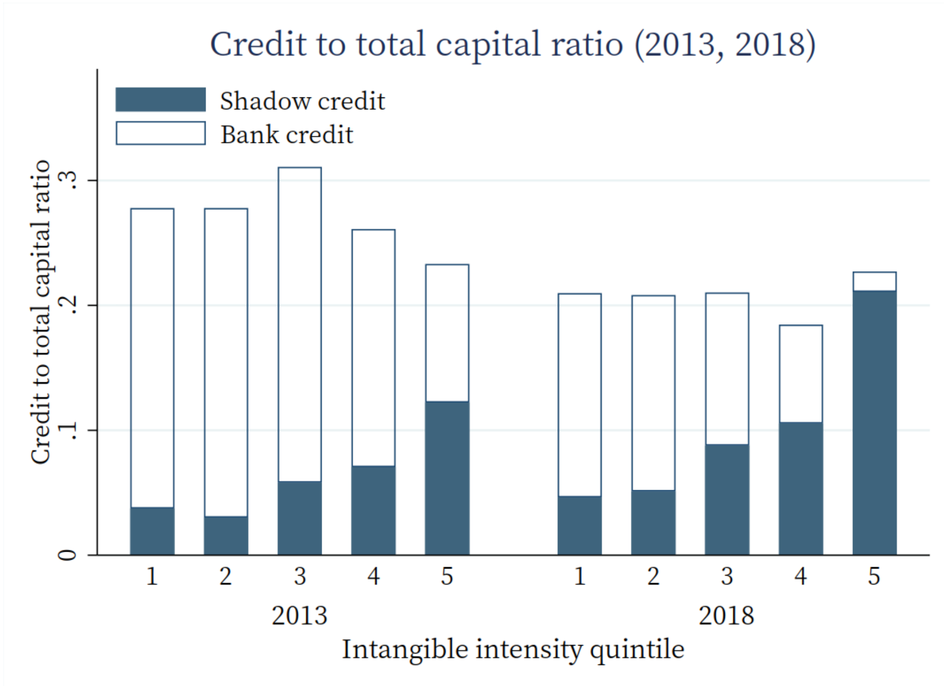


Figure 3: Fraction of credit to total capital by intangible intensity, 2013 and 2018

Note: Each credit to total capital ratio is a median of intangible intensity quintile. Shadow and bank credit is calculated by multiplying median fraction of shadow credit to the median total credit to capital ratio.

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. We will seek to understand the implications of this observation by embedding it in our model in Section 4.

3 Empirical Analysis

Using the data and measurements described in the previous section, we first analyze what factors affect the degree of shadow financing. In particular, we formally establish the association of the fraction of shadow credit with intangible intensity, productivity, and firm size. Then, we investigate the impact of the exogenous change in bank regulation on the borrowing patterns of firms with different intangible intensity level, and on their real outcomes.

3.1 Productivity, intangibles, and shadow financing

To formally establish the link between firm intangible intensity and its reliance on non-bank financing, we regress the fraction of shadow credit ($frac.shadow_{it}$) against intangible intensity ($intang.intensity_{it}$), while controlling for measured TFP and log total capital amount ($ln\ tot.cap_{it}$). Additionally, we control with firm fixed effects (f_i) and a post-reform dummy ($post.reform_t$), which is 1 if year t is after the introduction of new banking regulations (Basel III) in 2016 and 0 otherwise, and include its interaction with intangible intensity:

$$\begin{aligned} frac.shadow_{it} = & f_i + \beta_1 \cdot intang.intensity_{it} + \gamma \cdot ln\ TFP_{it} + \psi \cdot ln\ tot.cap_{it} \\ & + \beta_2 \cdot intang.intensity_{it} \cdot post.reform_t + \phi \cdot post.reform_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where the results are summarized in Table 1.

Table 1: Shadow financing, intangibles, and productivity

VARIABLES	(1) *frac.shadow*	(2) *frac.shadow*	(3) *frac.shadow*	(4) *frac.shadow*
intang.intensity	0.291***	0.251***	0.145*	0.088
	(0.034)	(0.038)	(0.086)	(0.094)
post.reform	0.0751***	0.045***	0.020*	
	(0.007)	(0.013)	(0.012)	
intang.intensity $\times$ *post.reform*		0.071**	0.144***	0.126***
		(0.029)	(0.026)	(0.036)
ln tot.cap	-0.020***	-0.020***	-0.079***	-0.110***
	(0.00535)	(0.00535)	(0.0254)	(0.0286)
ln TFP	0.023***	0.023***	0.000	0.002
	(0.005)	(0.006)	(0.005)	(0.005)
Observations	9,235	9,235	9,149	9,141
Fixed effects	None	None	Firm	Firm, Ind*Yr
R2	0.100	0.100	0.760	0.771

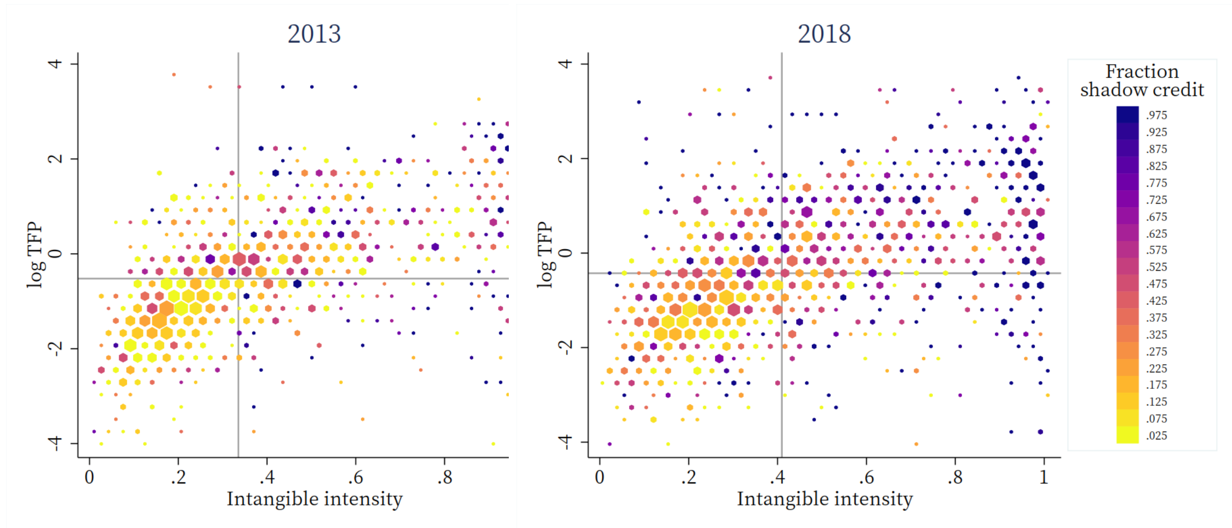
Note: All standard errors (in parentheses) are clustered at the firm level. *** p<0.01 ** p<0.05 *p<0.1

The regression results show that overall, firms with high intangible intensity and productivity tend to borrow more from non-banks, and large firms by their capital size borrow more from traditional banks. Columns (1) and (2) in Table 1 show that a 1 pp. increase in intangible intensity is associated with a 0.25-0.29 pp. increase in the fraction of shadow credit, while a 1 percent higher productivity is associated with around 2.3 basis points increase in the shadow credit fraction. On the other hand, a 1 percent larger amount of total capital, which includes both tangible and intangible assets, correlated with a 2 bp reduction in the shadow fraction. Both columns show that since 2016, which is the year when commercial banks are subject to a higher level of minimum capital requirement ratios, more credit is extended by shadow banks relative to traditional banks. Moreover, this tendency intensifies especially for the firms with higher intangible intensity since 2016, as the interaction term ($intang.intensity \times post.reform$) shows. Finally, columns (3) and (4) show that once firm fixed effects and (2-digit industry) $\times$ year fixed effects are included, cross-sectional differences in intangible intensity before the reform in 2016 and productivity do not have significant power to predict the fraction of shadow credit. However, the interaction term shows that within a firm, a 1 pp. increase of intangible intensity in the post-reform era leads to a 0.13 pp. to 0.14 pp higher shadow credit fraction. This indicates that intangible-intensive firms have disproportionately gravitated towards shadow lenders and away from traditional banks as the main source of credit.

In order to visualize the above results, Figure 4 plots the fraction of shadow credit by intangible intensity (x-axis) and log TFP (y-axis) at the beginning and end of the sample period. On the left panel of Figure 4, bottom left quadrant are the firms with bottom 50% intangible intensity and bottom 50% log productivity in 2013. These less-productive and less-intangible-intensive firms tend to borrow little fraction of their credit from shadow lenders, as the light colors of the hexagons represent. In particular, the upper right quadrant firms, which are more productive and intangible-intensive firms, tend to have higher fraction of shadow credit, as the darker colors on the plot show. Comparing the right panel, which plots firms in 2018, to the left panel of 2013, we highlight two observations. First, firms on average borrow more from shadow lenders, as the colors overall get darker on the right panel. Second, such pattern is magnified especially for the upper-right quadrant, where intangible-intensive and productive firms are plotted. In addition, both panels visualize the positive correlation between firms' productivity and intangible intensity, which higher mass of firms in first and third quadrants.

3.2 Differential effects of bank regulation by intangible intensity

In this section, we show that changes in the mode of financing across firms described in the earlier section are caused by the banking regulation reform. We do so by using our



(a) Interest rate on loans

(b) Interest rate on deposits

Figure 4: Fraction of shadow credit by TFP and intangible intensity

Note: Vertical gray lines are medians of intangible intensity in 2013 and 2018, respectively. Horizontal lines are medians of log TFP in corresponding years. Top and bottom 1% of log TFP observations are winsorized. Each hexagons are scaled by the number of firms of corresponding bin.

lender-firm matched credit data at the quarterly frequency. More specifically, we measure changes in bank and shadow credit growth over time by intangible intensity quintile, controlling for the firm and lender fixed effects as well as other control variables. By using the two-way fixed effects on both firms and banks, we control for any unobserved characteristics on the demand and supply of credit. For other control variables, we include firm characteristics such as total factor productivity and lagged total capital in log, and a lender-firm relationship variable such as each firm's lagged share in a lender's total credit portfolio. We pay particular attention to firms in the top and bottom 20% of intangible intensity (henceforth High and Low intangible intensity, respectively), and contrast their changes in bank and shadow credit growth.

Bank credit As a first step, we restrict our credit sample so that only commercial banks are included as lenders. In equation (2), we describe our regression explicitly. For each firm i and bank j pair in quarter t, we regress log differences in bank credit ($\Delta \ln bank\_credit_{ijt}$) on firm fixed effects (f_i), bank fixed effects (f_j), an intangible intensity quintile dummy variable for each firm i at time t ($q.intang.intensity_{it}$), and importantly an interaction term between time and intangible intensity quintile dummies ($\gamma_t \cdot q.intang.intensity_{it}$).[6] The main coefficient of interest is γ_{qt}, which measures the differences in bank credit growth for each intangible intensity quintile q in each quarter t, compared to the initial time period (2014q2).[7] In addition, β_q measures initial period differences in bank credit growth rates across intangible intensity quintiles q, relative to the 1st quintile which is chosen as the baseline. Finally, X_{ijt} includes other control variables as described in the above paragraph.

$$\begin{aligned}\Delta \ln bank\_credit_{ijt} = & f_i + f_j + \beta_q \cdot q.intang.intensity_{it} \\ & + \gamma_{qt} \cdot q.intang.intensity_{it} + \Psi X_{ijt} + \varepsilon_{ijt} \qquad (2)\end{aligned}$$

Figure 5 summarizes the results of running the above regression. We highlight the estimated values of γ_{qt} for two extreme cases, namely the 1st (Low) and the 5th (High)

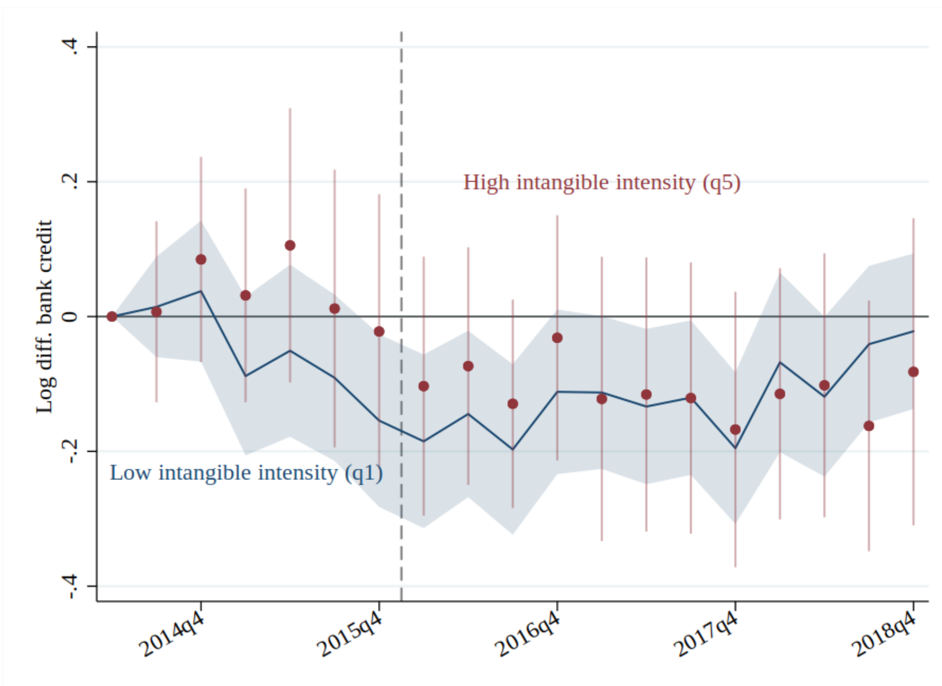


Figure 5: Growth of bank credit by intangible intensity quintile

Note: Beginning of the sample period (2014q2) is used as the baseline in each intangible intensity quintile.

[6]While our credit data is at the quarterly frequency, our firm-level data is annual. We match the firm-level annual data (end-of-year) to the year of each quarter.

[7]Notice that our credit data sample begins from 2013q2, but as an annual growth measure the first observation starts from 2014q2.

quintile of intangible intensity in each year.[8] In this figure, only Low intangible intensity firms experience significant decline in the bank credit growth, in contrast to the High intangible intensity firms whose changes are not statistically significant over the sample period. More specifically, compared with the pre-reform period (time period before 2016q1, the vertical dashed line), bank credit growth of Low intangible intensity firms (navy solid line) declines by up to 20% right after the reform, and the confidence interval (navy shaded area) is below its initial level (0, navy horizontal dashed line) at the onset of the reform in 2016. On the other hand, High intangible intensity firms experience relatively mild and not statistically significant changes in their bank credit growth compared to the initial period (maroon dots are point estimates and maroon vertical lines are 95% significance intervals in each quarter). In fact, the average growth rates are significantly lower for High intangible firms compared to the Low intangible firms, by about 27%, as the left panel of Appendix Figure 22 shows. This reflects systemic differences in bank financing by intangible intensity, potentially due to their differential availability of collateralizable assets. However, this reliance on hard collateral also implies that despite the initial advantage in bank financing, Low intangible intensity firms were affected by bank credit tightening the most. As a result, they experienced the most significant decline in bank credit growth compared to others.

Shadow credit As a next step, we run an analogous regression as in the Bank credit part, but this time we restrict our sample to shadow credit only. Equation (3) describes the regression, which is analogous to equation (2) except that the left hand side is now log differences in shadow credit at the firm-lender-quarter level ($\Delta \ln shadow\_credit_{ijt}$).

$$\begin{aligned}\Delta \ln shadow\_credit_{ijt} =& f_i + f_j + \beta_q \cdot q.intang.intensity_{it} \\ & + \gamma_{qt} \cdot q.intang.intensity_{it} + \Psi X_{ijt} + \varepsilon_{ijt}\end{aligned} \tag{3}$$

Figure 6 summarizes the estimated values and 95% confidence intervals of γ_{qt} for High intangible intensity firms (maroon solid line and shaded area) and Low intangible firms (navy dots and vertical lines). Compared to the bank credit growth rates, there are no significant differences in the initial period shadow credit growth rates (β_q) as described in the right panel of Appendix Figure 22.

The results show that High intangible intensity firms experienced a significant increase in their shadow credit growth rates, as much as 20% in 2017. The shadow credit growth for

[8] A figure summarizing for all other quintile can be found in the Appendix (Figure 21)

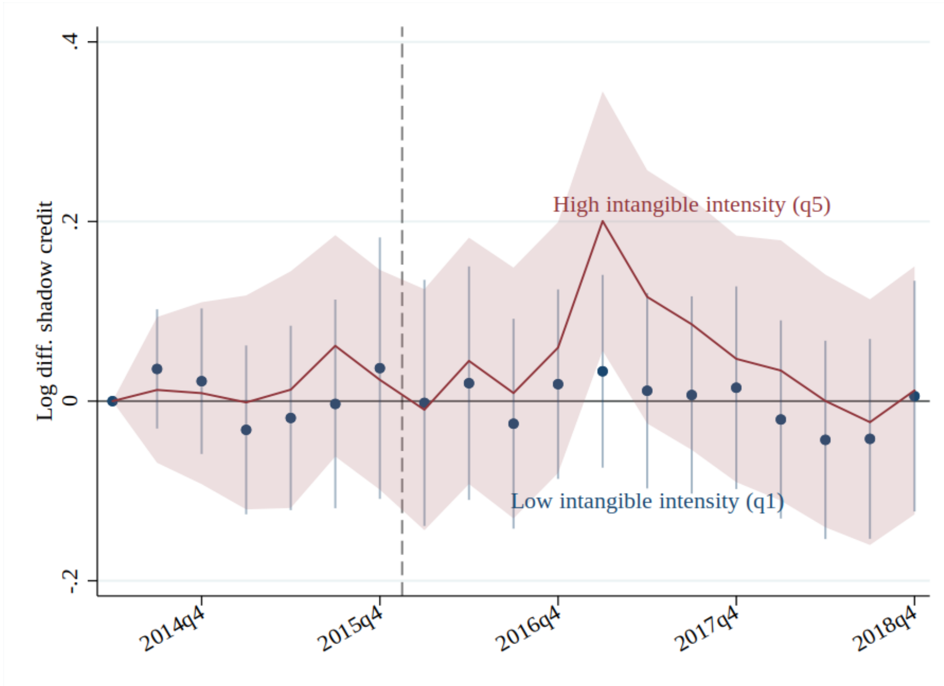


Figure 6: Growth of shadow credit by intangible intensity quintiles

Note: Beginning of the sample period (2014q2) is used as the baseline in each intangible intensity quintile.

Low intangible intensity firms, on the other hand, does not show any significant changes over the entire sample period. Why would a reform that directly impacted then regulated banks have a positive impact on High intangible intensity firms' non-bank credit growth? Lee, Lee and Paluszynski (2022) show that the Basel III implementation in Korea was accompanied by a significant increase in the supply of non-bank credit, driven by the general equilibrium effect of the reform. Here, we argue that the main beneficiaries of this expansion were the High intangible intensity firms, while the traditional tangible-heavy one were unable to use this channel to compensate for their losses of regulated bank credit.

In summary, depending on the degree of intangible intensity, the reform in banking sector affected firms differently. Firms with mostly tangible capital, who traditionally rely more on bank lending, experienced the most severe tightening in their bank credit as a result of the reform, without any significant increase in shadow financing. On the other hand, highly intangible intensive firms are mostly unscathed by the introduction of new banking regulations and raised more financing from shadow lenders after the reform. As a result, we observe a disproportionate increase in the fraction of shadow financing among highly intangible intensive firms since 2016, as described in earlier sections.

3.3 Real effects and shadow financing

As a final piece of our empirical analysis, we study the effects of firms' reliance on shadow financing on their real outcomes such as output or investment. As described in equation (4), we estimate the correlation of firm-level growth measures (Δy_{it}) on the lagged fraction of shadow credit before the reform ($frac.shadow_{i,t-1}$) and after the reform ($frac.shadow_{i,t-1} \times post.reform_t$), where $post.reform_t$ is a dummy variable whose value is equal to 1 from 2016 to 2018 and 0 otherwise. We use four different growth measures, namely log differences in net sales, total capital, tangible assets, and intangible capital. In order to control for any unobserved confounding effects, we include firm fixed effects (f_i) and (2-digit industry$\times$year) fixed effects (f_{jt}), as well as other control variables X_{it} such as the lagged level of dependent variable $y_{i,t-1}$ and total factor productivity.

$$\Delta y_{it} = f_i + f_{jt} + \beta \cdot frac.shadow_{i,t-1} + \gamma \cdot frac.shadow_{i,t-1} \cdot post.reform_t + \Psi X_{it} + \varepsilon_{it}. \tag{4}$$

The results of running the above regressions are reported in Table 2. It shows that a 1 pp. increase in the fraction of shadow credit is associated with a decrease in growth measures before the reform, ranging from 5 basis points for intangible capital to nearly 8 bp for the net sales growth rate. This is intuitive given that financing investment or production with collateralized bank credit is easier than with bond issuance. However, the results also show that starting from 2016, the relationship between growth and shadow financing reverts. After the reform, an increased usage of shadow credit is associated with superior

Table 2: Firm-level growth and shadow financing

	(1)	(2)	(3)	(4)
VARIABLES	$\Delta \ln\_net\_sales_t$	$\Delta \ln\_total\_capital_t$	$\Delta \ln\_tangible\_assets_t$	$\Delta \ln intan\_capital_t$
$frac.shadow_{t-1}$	-0.0763***	-0.0516*	-0.0570	-0.0498***
	(0.0260)	(0.0290)	(0.0386)	(0.00872)
$post.reform$	0.0440*	0.0512*	0.104***	0.0307***
$\#frac.shadow_{t-1}$	(0.0227)	(0.0263)	(0.0358)	(0.00800)
Observations	10,030	10,044	10,036	9,138
FE	Firm, Ind*Yr	Firm, Ind*Yr	Firm, Ind*Yr	Firm, Ind*Yr
R2	0.598	0.513	0.435	0.735

Note: All standard errors (in parentheses) are clustered at the firm level. *** p<0.01 ** p<0.05 *p<0.1

growth outcomes; most notably the tangible asset growth rate is higher by 10 basis points. This result conveys an straightforward interpretation of the effects of the reform. The exogenous change in regulation causes traditional banks to severe their credit provision to Low intangible intensity firms. On the other hand, the simultaneous boom in the non-bank credit supply mostly benefits the High intangible intensity firms. As a result, the natural advantage in real outcomes that Low intangible firms typically enjoy due to their ability to use hard collateral is significantly limited or outright erased.

4 Model

In this section we develop a dynamic model of heterogeneous firms who face a collateral constraint. Time is discrete, indexed by t, and goes until infinity. There is no aggregate uncertainty.

4.1 Firms

Preferences There is a continuum of heterogeneous firms with a unit mass in the economy, indexed by j. They have linear preferences over an uncertain dividend stream given by

$$\mathbb{E}_0 \sum_{t \geq 0} \beta^t d_t^j \tag{5}$$

The discount factor is given by $\beta \in (0, 1)$.

Portfolio choice At the decision stage of each period, a firm arrives with a cash-on-hand variable x_t^j. This wealth must be spent on dividend payout d_t^j, next-period capital k_{t+1}^j, or next-period financial asset a_{t+1}^j.

Production technology We assume that every firm has access to a decreasing returns to scale production function $f(z, k, n)$. This technology transforms k units of physical capital and n units of hired labor into the consumption good; a fraction δ of physical capital depreciates in the process. We assume that the production function is of the form

$$f(z, k, n) = z^{1-\nu}(k^\alpha n^{1-\alpha})^\nu$$

Following Lucas (1978), we introduce an firm-specific fixed factor z with a span-of-control parameter $\nu < 1$. We assume that z is a random variable and follows a Markov process with transition matrix Π_z. In every period, taking as given a realization of z^j_t, a pre-installed level of capital k^j_t, and wage w, each firm hires labor to maximize profit

$$\pi(k^j_t, z^j_t) = \max_n \left\{ f(z^j_t, k^j_t, n) - w_t n \right\} \tag{6}$$

Intangible capital We assume that each firm has an idiosyncratic share of intangible capital denotes as ψ^j_t. In other words, fraction ψ^j_t of the firm's capital k^j_t consists of intangible assets. Examples of such assets are brands, software, firm-specific human capital and other forms of *know-how*. For simplicity, we assume that the share of intangible capital that every firm uses in its production process is exogenous.[9] We further assume that ψ is a random variable and follows a Markov process with transition matrix Π_ψ.

Financial asset Each firm has access to a saving or borrowing technology via a non-contingent financial asset a^j_{t+1}. In the case of borrowing, the entrepreneur first turns to commercial banks where it can secure loans at the interest rate of r^b, up to the limit of $\underline{a}_b - \theta(1-\psi)k'$. The borrower can request an unsecured loan up to a fixed amount $\underline{a}_b$. Any loan beyond this amount must be collateralized with the newly invested capital. Fraction $1-\psi$ of the total capital stock is tangible and can potentially be seized by the lender. Parameter θ further represents the collateral constraint imposed by the regulators.

Borrowing from shadow banks If the firm is unable to borrow more funds from commercial banks, they can obtain additional loans up to the limit of $\underline{a}_s$ from shadow lenders. Such loans do not require a collateral but come at a higher interest rate of $r^s > r^b$. In the end, the effective interest rate paid on the entrepreneur's debt will be a combination of the two rate, depending on the proportion of loans borrowed from regulated and shadow banks.

The assumption of higher interest rate on shadow credit than on bank loans is directly supported by the data from the period of Basel III implementation in Korea (2013-2018). Appendix C presents the available evidence in more detail.

[9] A number of papers develop detailed models of endogenous investment in intangible assets, e.g. McGrattan (2020) or Falato et al. (2020). In our paper, we intentionally keep this characteristic exogenous (and informed by our data), which allows us to focus on understanding the selection into the sources of financing.

4.2 Recursive Formulation

In this section, we express the model in recursive formulation which we will use directly to compute the solution. For notational convenience, we suppress the entrepreneur and time subscripts.

Dynamic problem An entrepreneur solves the following dynamic programming problem

$$V(x,z,\psi) = \max_{d>0,k'>0,a'\geq a_b(k',\psi)+\underline{a}_s} d + \beta \mathbb{E}_{z',\psi'} \Big[V(x',z',\psi')|z \Big] \tag{7}$$

$$s.t. \;\; x = d + a' + k' \tag{8}$$

$$x' = \pi(k',z') + (1-\delta)k' + \Big(1 + r(a')\Big)a' \tag{9}$$

$$r(a') = \begin{cases} r^b, & \text{if } \; a' \geq a_b(k') \\ r^b \cdot a_b(k')/a' + r^s \cdot (a' - a_b(k'))/a', & \text{if } \; a' < a_b(k') \end{cases} \tag{10}$$

$$a_b(k',\psi) = \underline{a}_b - \theta(1-\psi)k' \tag{11}$$

A firm in our model enters the decision stage of each period with three state variables: net worth x, idiosyncratic productivity z, and intangible share ψ. Current net worth x can be spent on dividend d, or investment in financial assets a' or physical capital k'. Next period net worth will consist of the firm's gross returns on the two types of assets. Equation (10) shows the effective interest rate the firms will get on their financial assets. In particular, if the firms borrows any amount from shadow banks, the effective interest will exceed the baseline rate offered by commercial banks, r^b.

The total borrowing limit that the firm faces is $a_b(k',\psi) + \underline{a}_s$, where the part of it coming from regulated banks, $a_b(k',\psi)$, depends on the level of *tangible* capital investment that can be pledged as collateral.

4.3 Stationary Distribution

We finish describing the model by computing a stationary distribution of entrepreneurs. This distribution is given by a stationary measure $\Lambda(x, z)$ such that

$$\Lambda\left(x', z', \psi'\right) = \sum_{z \in \mathcal{Z}} \sum_{\psi \in \Psi} \pi_z\left(z', z\right) \pi_\psi\left(\psi', \psi\right) \Lambda\left(g^{-1}\left(x', z, \psi\right), z, \psi\right) \quad \text{for all} \quad \left(x', z', \psi'\right) \tag{12}$$

where $g^{-1}\left(x', z, \psi\right)$ is the inverse law of motion for entrepreneur's wealth. Note that the equilibrium is partial and the interest rates are parameters.

5 Quantitative Analysis

In this section, we describe the calibration of our model and discuss the mechanics of the main policy functions and the stationary distribution. We then conduct an experiment where we tighten the collateral constraint in a fashion that mimics the introduction of Basel III in Korea. Finally, we perform a counterfactual exercise where the rise of shadow lending is suppressed in order to highlight the role of shadow lending in the aggregate economy.

5.1 Functional forms

The stochastic process for firms' business productivity is

$$log(z_{t+1}) = \rho_z log(z_t) + \sigma_z \epsilon_{z,t+1}$$

where $\epsilon_{z,t+1}$ is an i.i.d. normal innovation with mean zero and a standard deviation of one. The process is discretized using the Tauchen method.

Likewise, the stochastic process for firms' share of intangible capital is

$$\psi_{t+1} = (1 - \rho_\psi)\mu_\psi + \rho_\psi \psi_t + \sigma_\psi \epsilon_{\psi,t+1}$$

where $\epsilon_{\psi,t+1}$ is an i.i.d. normal innovation with mean zero and a standard deviation of one. In our solution of the model, we first construct the grid for ψ that corresponds to the quintiles for year 2013 presented in Figures 2 and 3. We then resort to the Tauchen method to construct the transition probabilities.

We solve the model numerically using global methods by iterating over the value function, and then aggregating agents to find the stationary distribution.

5.2 Calibration

Table 3 shows the calibration of the model. As is standard, we fix the values of several standard parameters, and we resort to estimation and moments-matching inform the more controversial ones. In particular, productivity parameters (ρ_z, σ_z) are estimated by first measuring TFP and running the following regressions across firms

$$\log(z_{i,t+1}) = f_i + f_{j,t} + \rho_z \log(z_{i,t}) + \sigma_z \epsilon_{z,t+1} \tag{13}$$

where f_i is firm fixed effects and $f_{j,t}$ is 2-digit industry$\times$time fixed effects. The stochastic process for intangible intensity is estimated by running a simple regression.[10]

Credit parameters $(\theta, \underline{a}_b, \underline{a}_s)$ and shadow loan interest rate (r^s) are calibrated by jointly matching the following moments: leverage ratio, fraction of secured corporate loans, fraction of shadow loans in 2013, and standard deviation of fraction of shadow loans in 2013. Leverage ratio is calculated as the ratio of total credit in the data to all assets. The calibration results in a good fit for the set of targets chosen, with the exception for the volatility of the share of shadow loans which falls short in the model.

5.3 Model mechanics

This section describes the basic intuition behind the mechanisms of the model.

Who borrows from shadow banks? Figure 7 presents the decision rule of entrepreneurs as function of the two state variables, wealth and productivity, for a fixed level of intangible intensity. Intuitively, agents who have low wealth and high productivity tend to borrow from shadow banks in addition to regulated banks. This result corroborates our empirical findings in Section 2.4 which shows that the less wealthy, and the most productive firms tend to use shadow credit disproportionately more.

[10] We do not include fixed effects in this regression because we aim to capture the full spectrum of heterogeneity in intangible intensity of production across all firms in our sample.

Table 3: Calibration of the parameters

Parameter	Meaning	Value	Source
β	Discount factor	0.96	Standard value
ν	Span of control	0.8	Standard value
α	Capital share	0.34	Labor share of 0.51
δ	Depreciation	0.08	Korean data
r^b	Bank interest rate	3.44	Korean data
ρ_z	Persistence of productivity	0.28	Firm data
σ_z	St. dev. of productivity	0.51	
μ_ψ	Mean of intang. intensity	0.49	Firm data
ρ_ψ	Persistence of intang. intensity	0.87	
σ_ψ	St. dev. of intang. intensity	0.08	
θ	Collateral constraint	0.30	Joint calibration
$\underline{a}_b$	Unsecured credit line: banks	-1.18	
$\underline{a}_s$	Unsecured credit line: shadow	-28.33	
r^s	Shadow interest rate	4.23	
Calibration targets		**Model**	**Data**
Leverage ratio (%)		30	31
% of secured corp. loans		52	54
% of shadow loans (2013)		37	36
St. dev. % of shadow loans (2013)		23	37

Figure 7 also shows the effect of tightening of the collateral constraint, our main exercise in Section 5.4. As a result, the threshold for borrowing from shadow banks expands rightwards, which implies that there are more "shadow borrowers" in the economy. The next section investigates the heterogeneous effects of such financial frictions on the propensity to use shadow credit for firms of various sizes.

Structure of firms' credit Figure 8 presents the model-generated counterpart to Figure 3. As in the data, we observe that the total usage of credit relative to capital is declining in intangible intensity, while the fraction of shadow credit is rising. In relation to our baseline reform exercise in Section 5.4, the right-hand side panel of Figure 8 also shows what happens in the aftermath of the reform in our model. Consistent with the evidence presented in Figure 8, there is a general credit crunch in the economy that mostly impacts *tangible-intensive* firms. By contrast, the intangible-intensive one are able to weather the tightening better by disproportionately increasing their reliance on shadow financing. In particular, consistent with the data, the top quintile of the most intangible-intensive firms experiences essentially no reduction in credit and relies almost entirely on non-bank

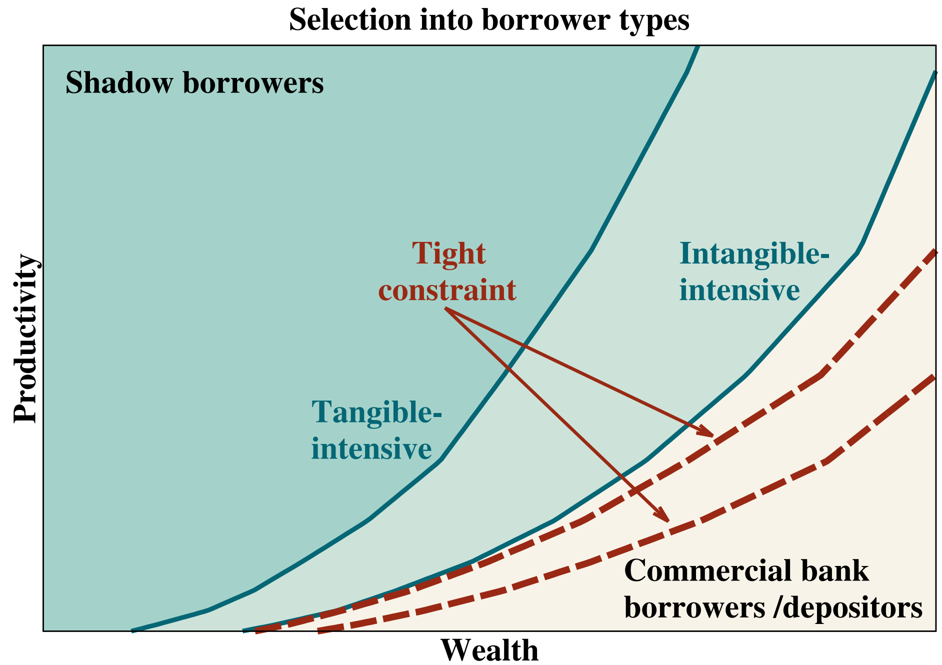


Figure 7: Endogenous selection into types of borrowers in the model

financing in the post-reform stationary distribution.

5.4 Main results: aggregate statistics

We now present our main model result in which we mimic the period of Basel III implementation in Korea by tightening of the collateral constraint on borrowers. Specifically, we conduct three exercises. First, we lower the parameter θ from the baseline value of

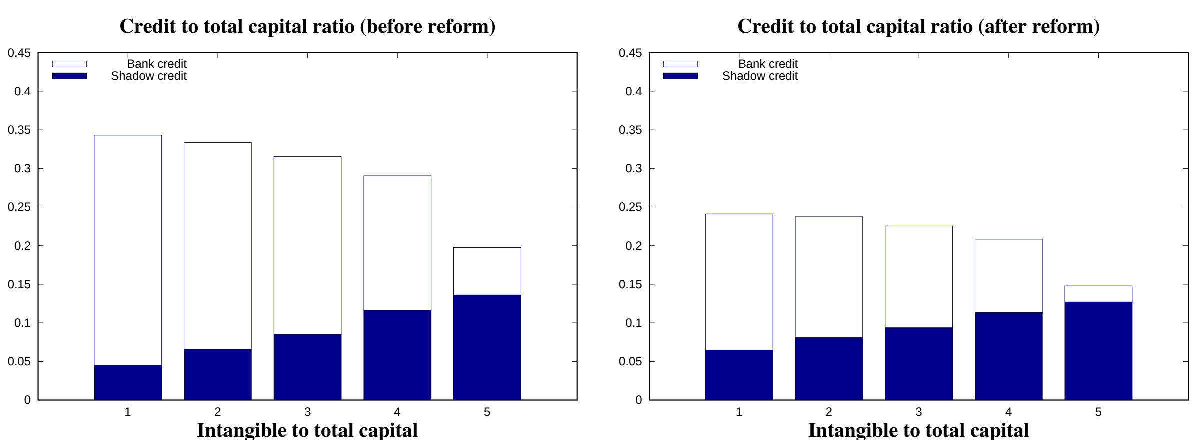


Figure 8: Fraction of credit to total capital by intangible share: model

0.3 to 0.2 and simultaneously tighten the bank unsecured credit $\underline{a}_b$ from -1.17 to -0.1. The "post-reform" parameters are calibrated to match the end-of-period leverage ratio of 21% and fraction of secured corporate loans of 46%. Second, we design a counterfactual scenario in which, along with the collateral constraint tightening, the government increases the interest rate on shadow loans to 4.34% (from the baseline of 4.23%) such that firms are deterred from taking excessive loans from shadow banks. This counterfactual scenario is motivated by the fact that the recent rise of shadow finance has been perceived by many as an unwelcome and potentially destabilizing force.[11] Third, as an alternative to the no-growth-in-shadow-credit policy response, we analyze a scenario in which all capital including intangible assets can be used as collateral for bank borrowing. Formally, this boils down to setting $\psi = 0$ for all firms in the model, effectively eliminating one of the state variables. While this scenario is extreme for simplicity, it mimic actual policy proposal from various countries that attempt to create an institutional setting for pledging certain intangible assets such as patents or software, as collateral.[12]

Table 4 summarizes the main macroeconomic indicators in the baseline stationary distribution and contrasts them with the results of our exercises. In the baseline, 37% of total credit is extended by shadow intermediaries. This fraction goes up to almost 53% as a result of the credit tightening. Entrepreneurs adjust their portfolio by reducing investment in capital and repaying debt, and hence they accumulate wealth. Along with this

Table 4: Main results

Aggregate Moments	**Pre-reform** $\theta = 0.3$ $r_s = 4.23\%$	**Post-reform** $\theta = 0.2$ $r_s = 4.23\%$	**Counter I** $\theta = 0.2$ $r_s = 4.34\%$	**Counter II** $\psi = 0, \theta = 0.2$ $r_s = 4.23\%$
% shadow loans	37.23	52.61	37.18	35.48
% shadow borrowers	75.81	74.91	51.61	78.33
% firm leverage	30.03	21.40	15.24	29.14
% secured loans	52.46	46.23	61.38	61.90
Wealth	29.2	32.09	34.22	29.62
Capital	36.37	36.07	35.98	36.55
Assets	-11.39	-8.37	-6.24	-11.24
Output	16.25	16.16	16.13	16.29

[11]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.

[12]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.

change, aggregate output drop slightly due to the lower stock of capital. It is notable that the fraction of firms who borrow from shadow lender remains roughly unchanged in the aftermath of the reform. Output declines by about 0.5% steady-state to steady-state which suggests that in the long run, firms are mostly able to replace the missing credit with their own equity.

When the interest rate on shadow credit increases along with the tightening of the credit constraint, we observe that entrepreneurs cut down on their borrowing even further and accumulate a higher amount of wealth compared to the baseline exercise. This time around, roughly one third of former shadow borrowers no longer borrow from that source. As a result, output declines further but the magnitude is still rather small (-0.75%) partly because the additional increase in the shadow interest rate is marginal (0.11 percentage points) compared to the baseline scenario.

In the second counterfactual, all capital is allowed to be pledged as collateral in addition to the baseline tightening of bank policy. We observe that the fraction of shadow credit drops by two percentage points only, while output and wealth increase slightly. While these long-term effects are small due to a shift in the ergodic distribution of the firms, Section 5.6 shows that they are much larger on transition in the short run.

5.5 Main results: distribution

Next, we investigate the distribution of shadow credit usage with respect to firms' intangible intensity as predicted by the model. Figure 9 plots the fraction of shadow financing by intangible intensity for the equilibrium before and after the tightening of the collateral constraint. Just as in the data presented in Section 2.4, we can see that the firms who rely on intangible capital more tend to borrow from shadow banks disproportionately more. Moreover, as the constraint gets tighter, this propensity becomes higher for all firms. The model does not generate the greater increase in shadow financing for the most intangible-intensive firms compared to the data. This suggests that the observe change in the slope observe in Figure 2 reflects a force other than the change in regulation. Figure 23 in the Appendix sheds some light on what this force may be. It shows that a majority of entry in our model occurs through the top intangible intensity quintile. This is also the group of firms that increase their reliance on shadow financing the most relative to the remaining ones in the aftermath of the reform. This suggests that a closer study of the interaction between firm entry and the modes of financing are an important component of this story.

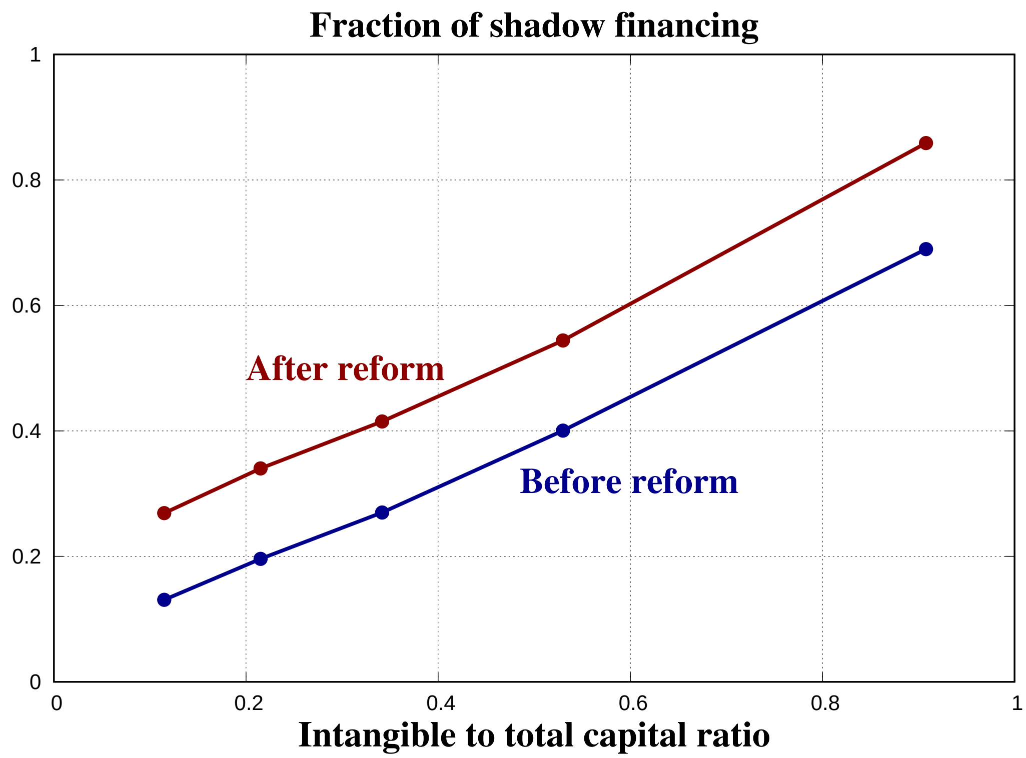


Figure 9: Fraction of shadow credit in the model by intangible intensity

On the other hand, Figure 10 presents the fraction of shadow financing following the tightening of the collateral constraint in the counterfactual scenario of no rise of shadow credit (the other counterfactual is not visualized because it assumes that intangible intensity is equal for all firms). Simultaneously with restricting the bank credit, the government takes actions that elevate the interest rate r_s to the extent that the average fraction of shadow financing in the economy remains constant at 37%. In that case, the least intangible-intensive firms reduce their usage of shadow credit almost entirely, but the most intangible-intensive ones continue to borrow significantly from shadow lenders.

5.6 Transitions

Finally, to evaluate the impact of the reform in the short run, we calculate transitions of the model economy from the pre-reform to the post-reform stationary distribution, for both baseline and counterfactual exercises. Figure 11 summarizes the transition paths for fraction of shadow loans, wealth, output, and capital to output ratio. Firms in the economy have perfect foresight and the once-and-for-all changes in credit constraints (and

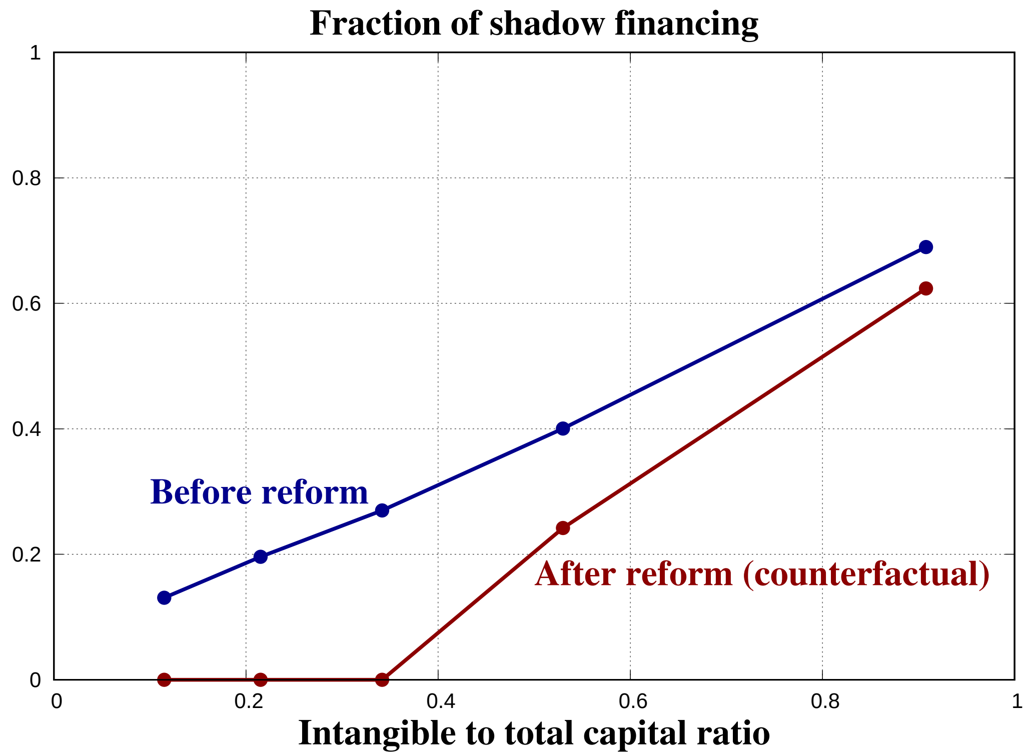


Figure 10: Fraction of shadow credit in the model by intangible intensity - counterfactual

shadow interest rate for the counterfactual exercise) are known to the agents in period 1.

On impact, firms immediately increase the fraction of shadow credit beyond the level of the new steady state and slowly adjust it to the new steady state. Notice that with the no-rise-of-shadow counterfactual exercise, while the new steady state of shadow credit fraction is calibrated to be the same as the pre-reform level, on the transition path there is still an overshooting of the shadow credit ratio. While the firms temporarily channeled a part of their original demand for credit to shadow lenders, the substitution between shadow and bank credit is not perfect and they cut down on their investment and hence production on impact. In the meantime, they accumulate more wealth by reducing their borrowings and invest less in capital, so that they can resume some of the bank borrowing under the tighter credit constraint. In the baseline scenario, output declines by up to 0.5% and then settles at a similar level in the long run. Under the counterfactual exercise where shadow credit interest rate is higher compared to the baseline scenario, the decline in out is larger and exceeds 1.5% in the short run, before eventually converging to about 0.75% below the pre-reform level. This shows that any potential enhancement in financial stability may come at a significant efficiency cost, especially in the short-run following the

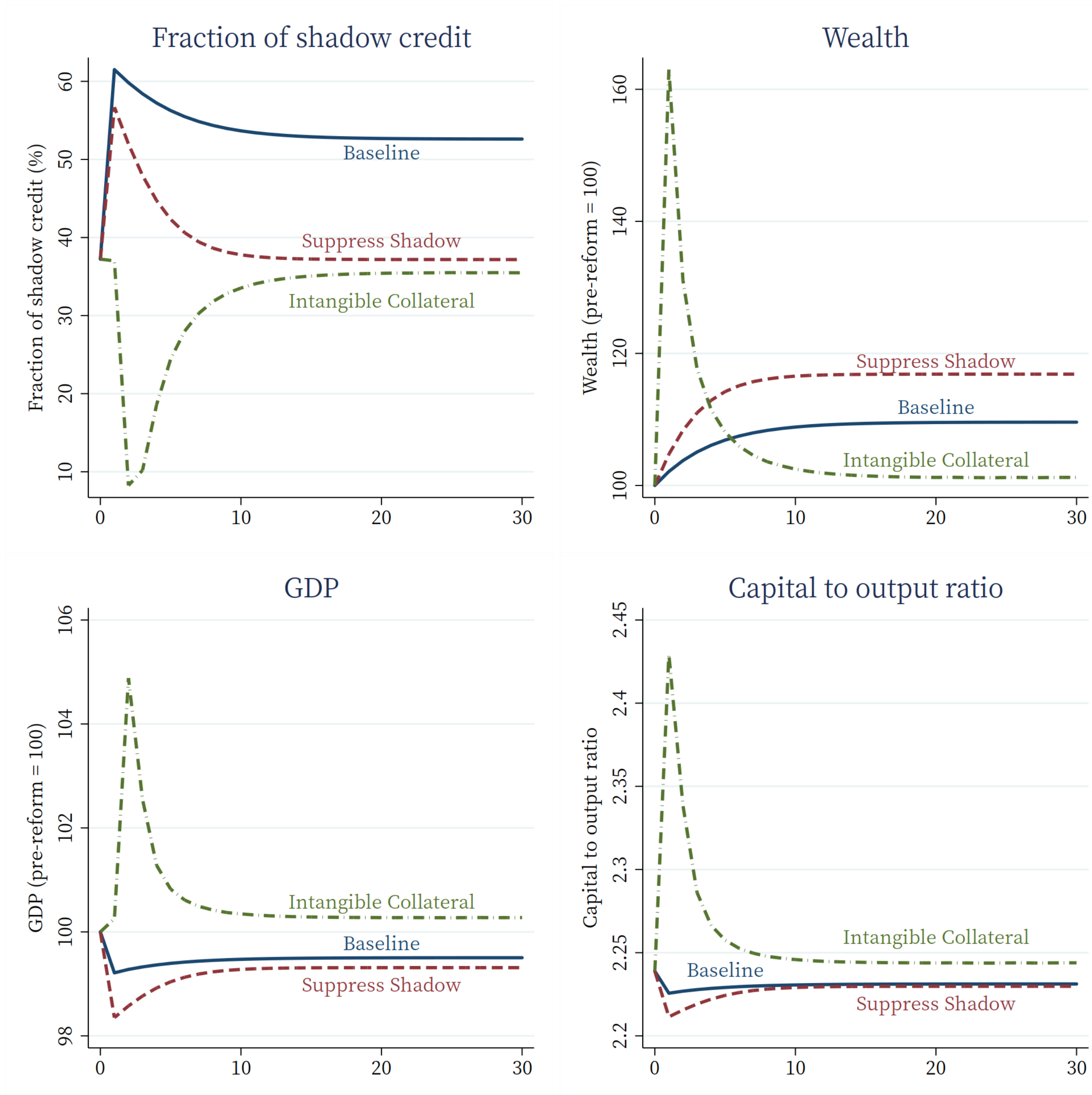


Figure 11: Transitions in the baseline and counterfactual reform scenarios

introduction of the reform.

Under the second counterfactual scenario, firms are allowed to to pledge all of their capital as collateral and, as a result, the reliance on shadow credit drops dramatically on impact. This is accompanies by a corresponding increase in wealth and output by up to 60% and 5%, respectively. In the long run, however, firms increase their dividend payouts substantially and return to borrowing from shadow lenders (because bank credit is still tightened following the reform), resulting in lower output and a fraction of shadow credit that is just below the pre-reform targeted moment.

5.7 Effects on output in the cross section

As a final step, we use the predictions from transitional dynamics to analyze the effects of credit tightening on real outcomes of firms in the model. Figure 12 plots median log output for each level of intangible intensity in the model for the periods corresponding to 2013 and 2018 (for both the baseline and counterfactual reform scenarios). As we document in the data in Appendix A.4, intangible-intensive firms tend to be smaller than the tangible ones. In the baseline reform scenario, however, this relationship gets weaker due to the fact that credit tightening affects primarily tangible-intensive firms (in the absence of general equilibrium effects). As a result, median output of the most intangible-intensive firms remains almost unaffected. This prediction is validated in Figure 13 where we compare growth rates of real output by intangible intensity. Both in the model and in the data, output generally decreases at all except for the highest level of intangible intensity (the scales are different due to the lack of growth in the model). Finally, turning back to Figure 12, the no-rise-of-shadow counterfactual exercise predicts the opposite pattern, with traditional tangible-based firms affected little, and the rest seeing their output levels

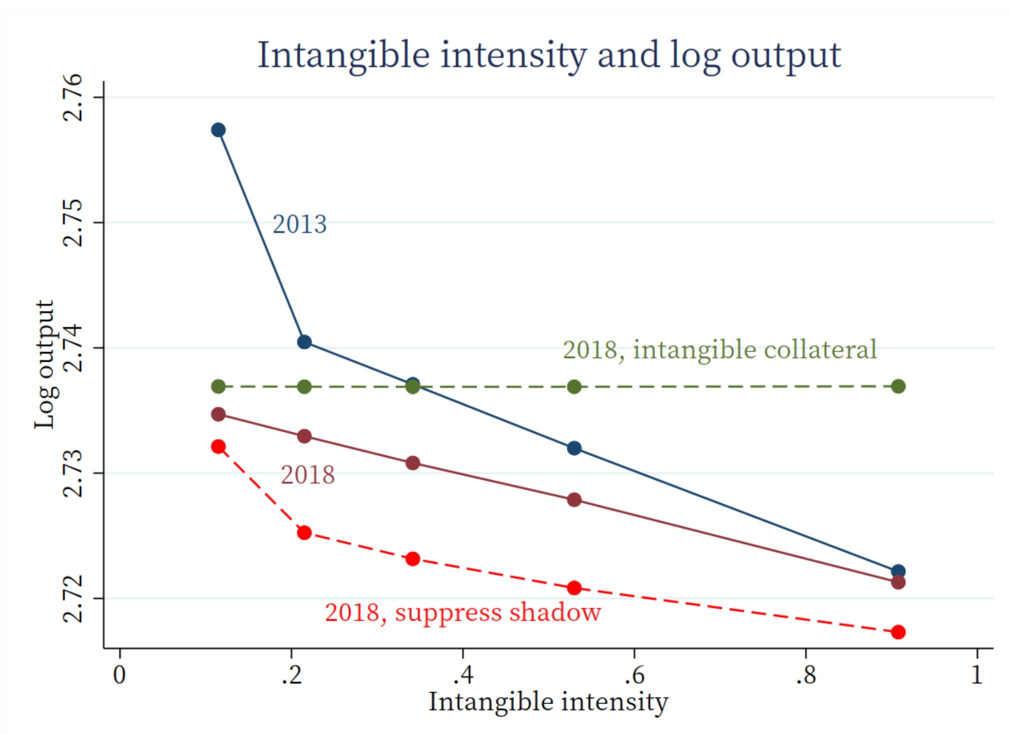


Figure 12: Output in the cross section of intangible intensity over transition

decline. The reason for this result is that in the counterfactual scenario, the regulators suppress the rise of shadow credit by making it more expensive. Hence, firms across the distribution have no choice but to shrink their production. The ones that rely more on tangible capital do so due to the tighter collateral constraint. The more intangible-intensive ones on the other hand face a higher cost of accessing this alternative means of financing. By contrast, under the second counterfactual scenario, all firms have identical output because intangible intensity is eliminated as a state variable.

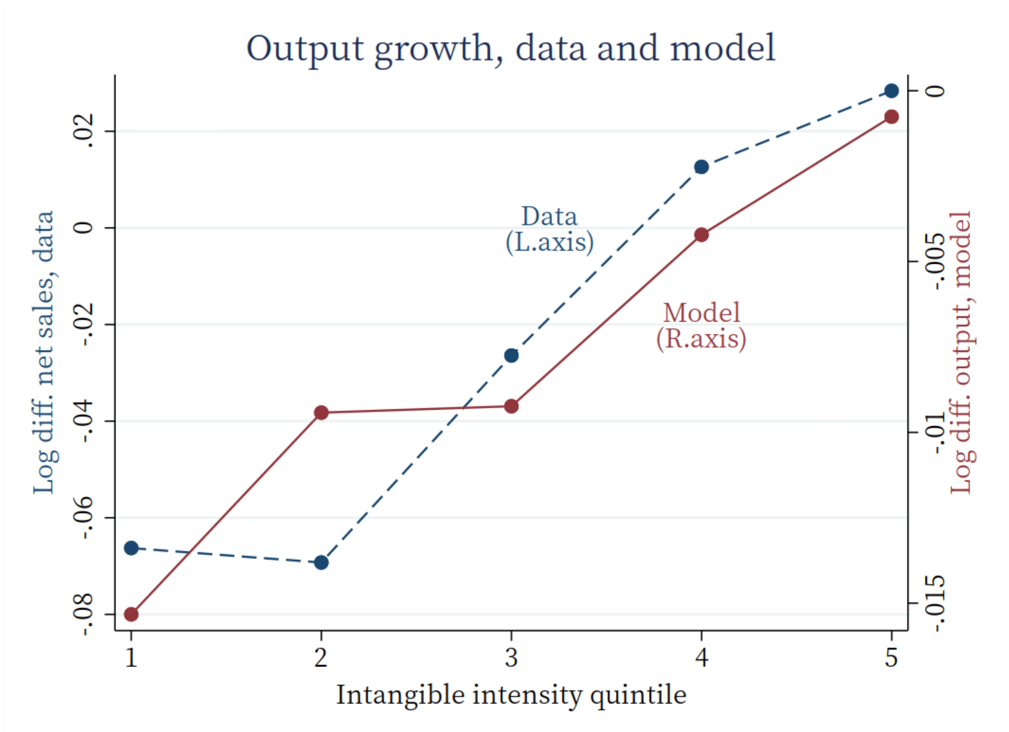


Figure 13: Output growth as function of intangible intensity - model vs. data

6 Conclusion

In this paper we use a new dataset on corporate credit from South Korea to document that firms that 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 Basel III banking regulation.

We explain these findings using a model of heterogeneous firms who have an option to borrow from shadow banks at a higher interest rate. As tighter collateral constraints prevent firms from securing loans from regulated banks, the shadow lenders step in and expand their share. Considering the distribution of firms, it is most productive and most intangible-intensive ones that tend to borrow from non-banks the most in response to financial frictions because their ability to post collateral on regulated bank loans is the lowest. Our model shows that any attempts to regulate shadow intermediaries may come at a significant efficiency cost to the economy.

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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)
  - General administrative expenses (124200)
  - Selling expenses (124300)
  - Research costs (124406)
  - Ordinary R&D cost (124410)
  - Ordinary development (124420)

Benchmark In the benchmark 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.

Alternative In the 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.

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 14 and 15 show. Alternative measures tend to be smaller than the benchmark, except for some large firms which may have more complete data of research and development expenses. Book values are often closer to 0, and much smaller than the benchmark estimation for most cases.

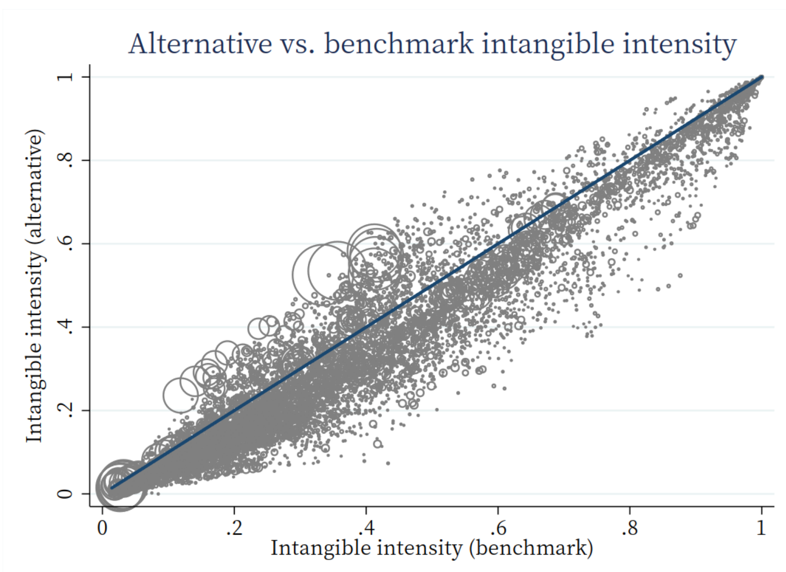

Figure 14: Alternative to benchmark intangible intensity

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.

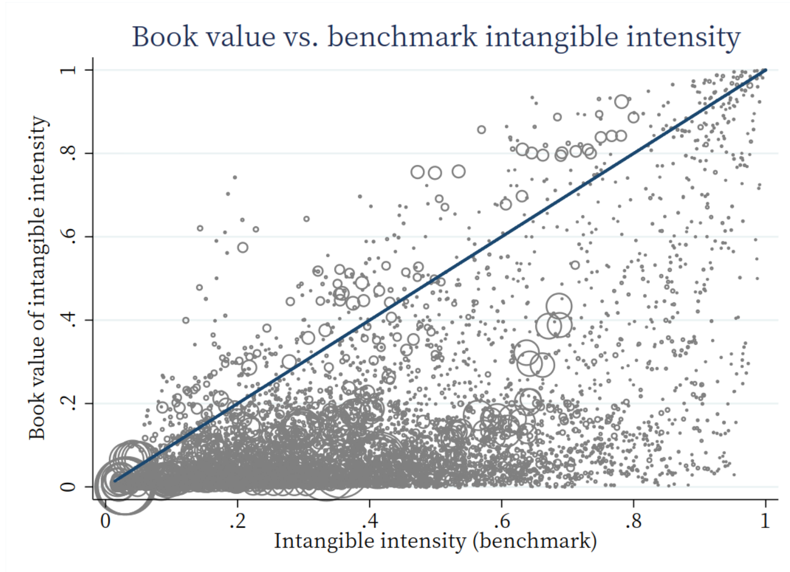

Figure 15: Book value to benchmark intangible intensity

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.

A.2 Distribution of intangible intensity

Based on the benchmark approach of intangible capital measurement, we calculate intangible intensity as a fraction of intangible capital over the sum of intangible capital and book value of tangible assets. Figure 16 shows the distribution of intangible intensity in 2013 and 2018, which correspond to the beginning and end of our sample period. We highlight two observations. First, in both years, intangible intensity shows bi-model distributions. There is a lower mode around 0.2 to 0.3, which are the group of low intangible intensity firms, and the other mode is extremely high, reaching nearly 1. Second, the overall distribution is moving towards higher levels over the years. Not only the lower mode is shifting right, the overall mean is increasing.

This rightward shift in intangible intensity distribution can be inspected from the quintile cutoff values. In Figure 17, we plot the thresholds for intangible intensity quintiles in each year. There is a monotonic increase in the cutoff values, and especially the top quintile shows significant elevation of the cutoff.

A.3 Characteristics of intangible-intensive firms

Based on the measured intangible capital and productivity, we document two of the key characteristics of our sample firms. First, we find that firms with high intangible inten-

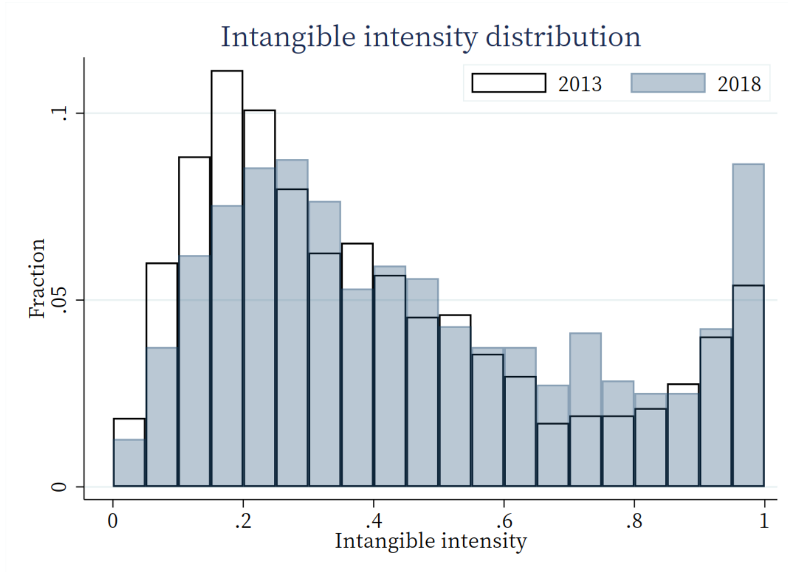

Figure 16: Distribution of intangible intensity, 2013 and 2018

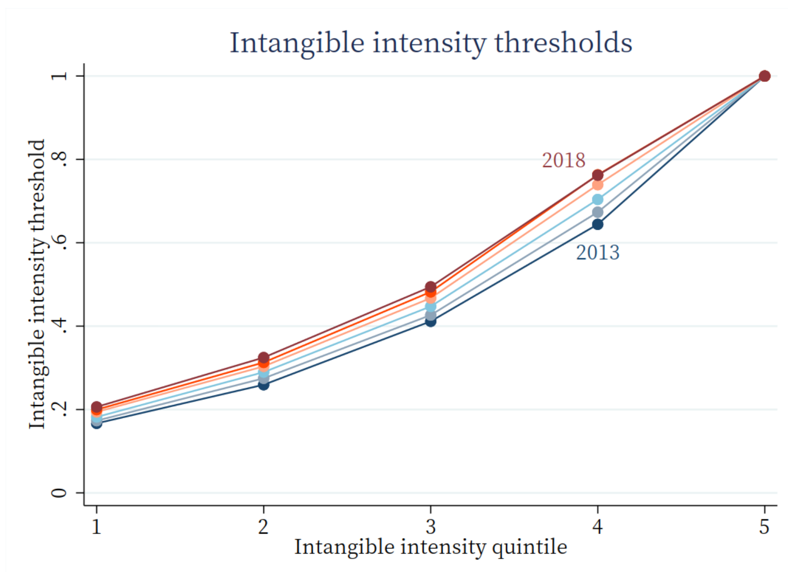

Figure 17: Intangible to total capital ratio quintile thresholds by year

sity (*intangible-intensive*) tend to be smaller in the total size of capital, which includes both tangible and intangible capital. Second, intangible intensive firms are on average more productive, with high measured TFP.

More specifically, Figure 18 describes the relationship with the size of capital and intangible intensity. The red predicted line in the figure shows that with a 1 percentage point increase in the intangible intensity, a median firm's total capital size decreases by nearly

2 percent. This pattern is robust to the inclusion of (year×2-digit industry) level fixed effects, and the magnitude stays around 2 percent (Table 6).

Secondly, firms with high intangible intensity tend to be more productive, based on the benchmark TFP measurement. Table 5 summarizes the correlation between intangible intensity and measured productivity, under different fixed effects. Columns (1) and (2) show that within a year or a (year×2-digit industry) level, firms with a 1 percentage point higher intangible intensity tend to be around 2 percent more productive. However, such patterns no longer hold once firm fixed effects are included, as the column (3) shows. This indicates that productivity and intangible intensity have strong correlations in the cross-section of firms, but not as much across time within a firm.

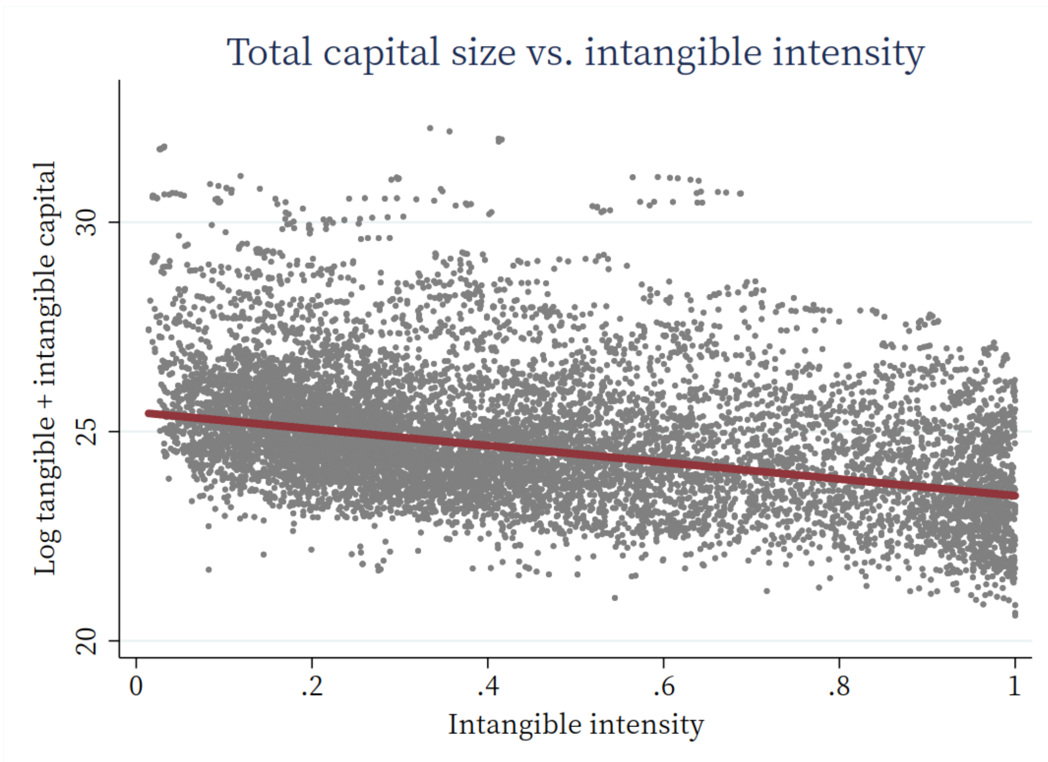

Figure 18: Log total capital to intangible intensity

Note: Intangible intensity is calculated as intangible capital to (intangible + tangible capital). Log tangible + intangible capital is the sum of measured intangible capital and book value of tangible assets, deflated to 2015 Korean Won, using a GDP deflator. Red predicted line is a quantile regression at median.

A.4 Additional figures and tables

Table 5: Productivity and intangible intensity

VARIABLES	(1) *ln TFP*	(2) *ln TFP*	(3) *ln TFP*
intang.intensity	2.897***	1.911***	-0.0486
	(0.113)	(0.0996)	(0.240)
ln tot.cap	0.0118	0.0362***	-0.0756
	(0.0173)	(0.0123)	(0.0820)
Observations	8,865	8,857	8,728
Fixed effecs	Year	Yr*Ind	Yr*Ind, Firm
R2	0.286	0.641	0.882

Note: Industry×Year fixed effects are at 2-digit Korean Standard Industry Classification (KSIC) level. All standard errors (in parentheses) are clustered at the firm level. *** p<0.01

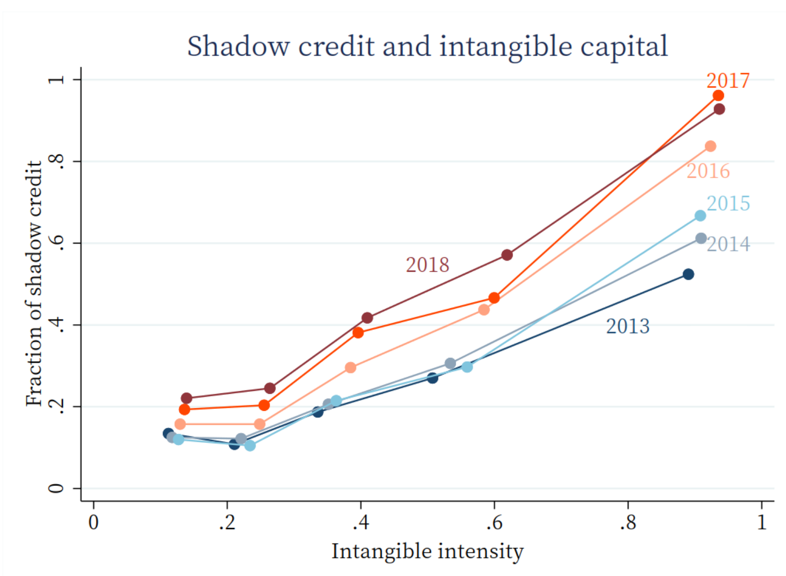

Figure 19: Intangible to total capital ratio and shadow credit ratio

Table 6: Log total capital against intangible intensity

VARIABLES	(1) *ln tot.cap*	(2) *ln tot.cap*	(3) *ln tot.cap*	(4) *ln tot.cap*
intang.intensity	-2.087***	-1.995***	-2.084***	-2.173***
	(0.0509)	(0.0552)	(0.0511)	(0.0618)
Observations	10,237	10,237	10,237	10,237
Fixed effecs	None	None	Year	Yr*Ind
Method	OLS	Quintile	OLS	OLS

Note: Standard errors are in parentheses. *** p<0.01

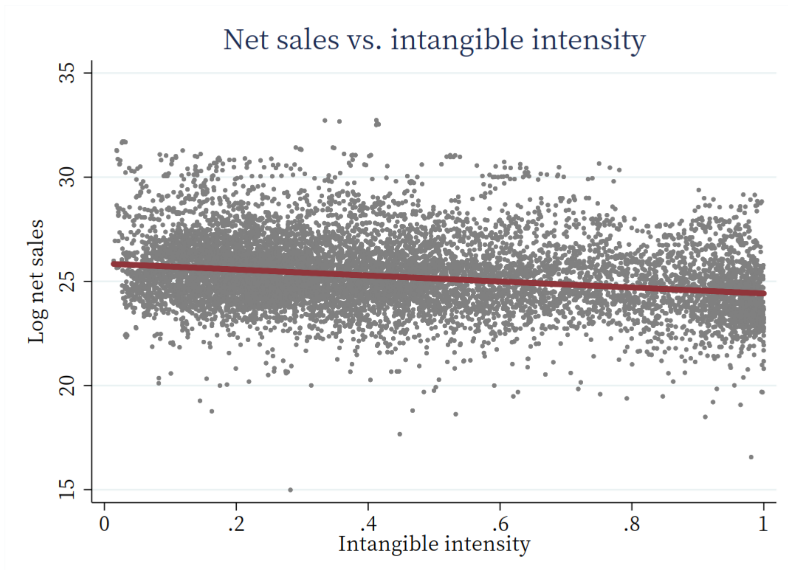

Figure 20: Net sales vs. intangible intensity

Table 7: Log net sales against intangible intensity

VARIABLES	(1) *ln sales*	(2) *ln sales*	(3) *ln sales*	(4) *ln sales*
intang.intensity	-1.470***	-1.435***	-1.447***	-1.133***
	(0.0575)	(0.0650)	(0.0576)	(0.0695)
Observations	10,219	10,219	10,219	10,219
Fixed effecs	None	None	Year	Yr*Ind
Method	OLS	Quintile	OLS	OLS

Note: Standard errors are in parentheses. *** p<0.01

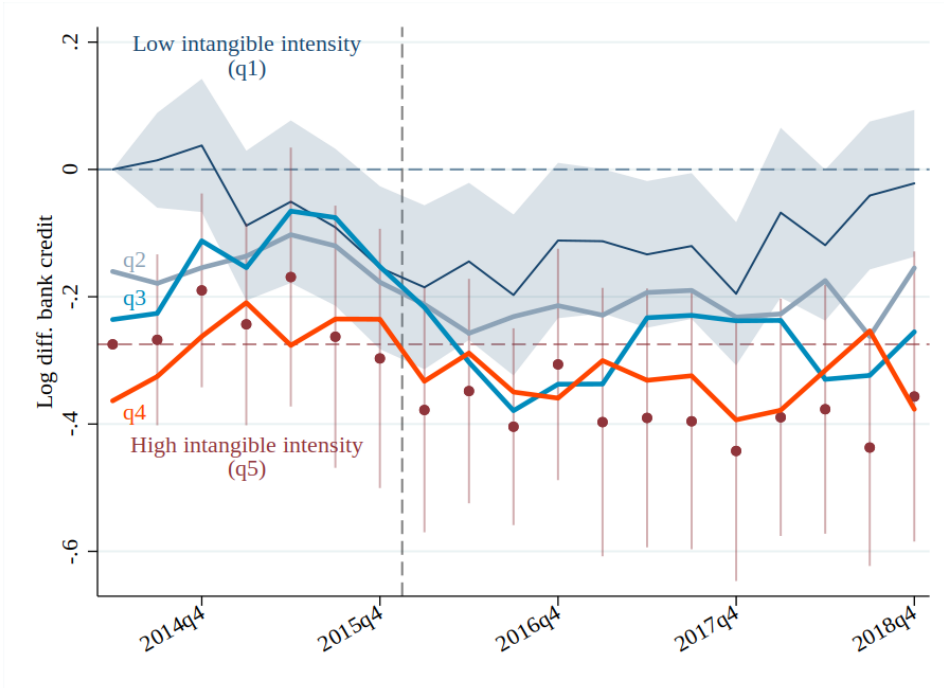

Figure 21: Bank credit growth by intangible intensity quintile

Note: Beginning of the sample period (2014q2) is used as the baseline in each intangible intensity quintile.

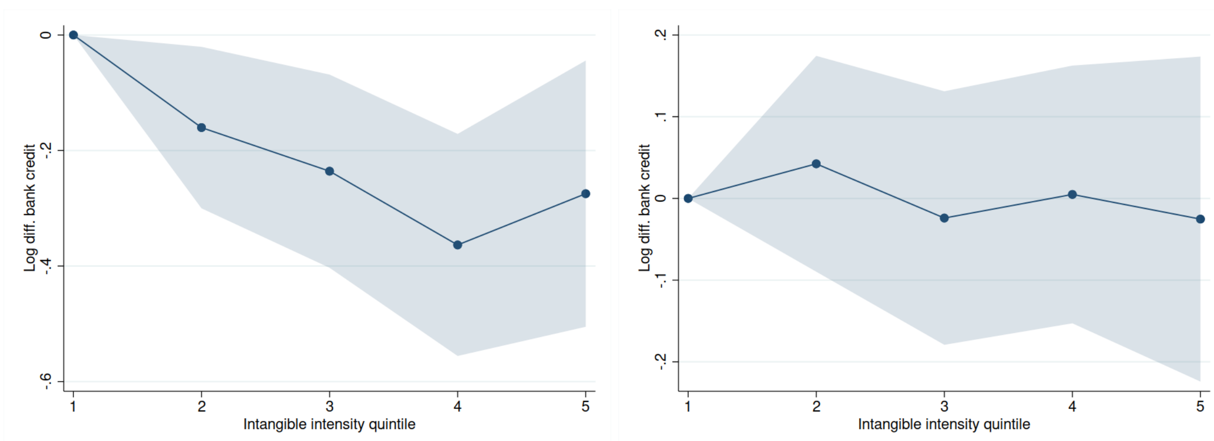

Figure 22: Average bank (left) and shadow (right) credit growth by intangible intensity quintile

Note: The first quintile (q1) is used as the baseline.

Table 8: Top 5 industries by intangible intensity quintiles

Industry (1-digit)	Frac	Cum.Frac
1st. Quintile		
Manufacturing	0.804	0.804
Transportation and storage	0.053	0.858
Professional, scientific and technical activities	0.031	0.889
Information and communication	0.025	0.914
Wholesale and retail trade	0.022	0.936
3rd. Quintile		
Manufacturing	0.789	0.789
Wholesale and retail trade	0.066	0.855
Professional, scientific and technical activities	0.046	0.901
Information and communication	0.040	0.941
Construction	0.032	0.973
5th. Quintile		
Information and communication	0.328	0.328
Manufacturing	0.266	0.594
Wholesale and retail trade	0.149	0.743
Professional, scientific and technical activities	0.125	0.868
Construction	0.074	0.942

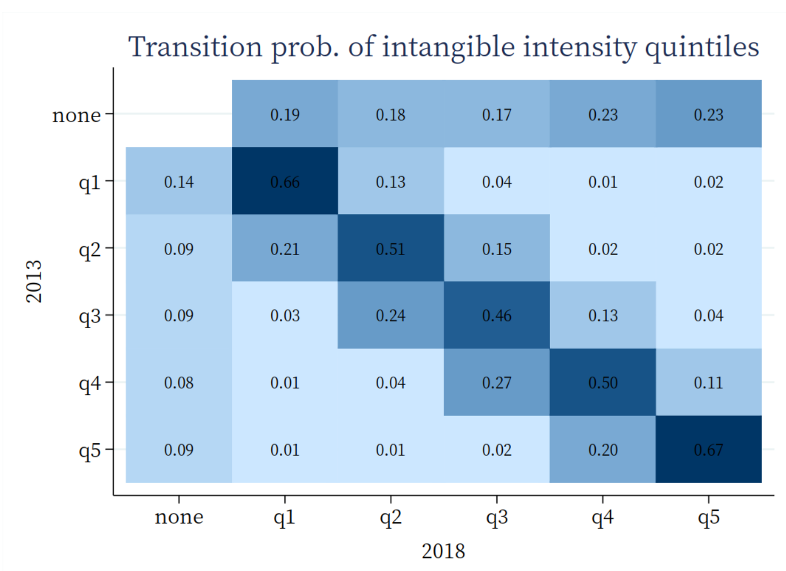

Figure 23: Transition probability of intangible intensity quintiles

B Productivity

B.1 Measurement

We measure TFP by subtracting the number of employee and gross capital stock from the amount of sales or value added (sales net of cost of sales), all in log scale. In the following, we describe the data source and measurement steps in more detail.

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

- sales : SALES(NET)[121000]
- no_employees : No. of Employees[105000]
- cost_of_sales : COST OF SALES[122000]
- wage_bills : Personnel expenses[124100]
- tang_assets : TOTAL TANGIBLE ASSETS[113200]
- tang_depreciation_etc : (Total Accumulated Depreciation_Tang.A.[113201]) + (Total customer's donation-tangible assets[113202]) + (Total government grants-tangible assets[113203]) + (Total reconciliation account for right to use_Tang.A.[113204]) + (Accumulated Impairment loss_Tang.A.[113205]).
- industry : Very Detailed Grouping[0A1135]

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.

From the Bank of Korea, we take GDP deflator measures for both expenditures and gross fixed capital formation (private).

Gross capital construction We use a perpetual inventory method in order to measure gross capital stocks. For the initial year $t = 0$ (which is set as the listed year or 2010, whichever is later), we measure the amount of gross capital stock as the sum of following variables:

$$Gross\_capital\_stock_0 = tang\_assets_0 + tang\_depreciation\_etc_0$$

For all subsequent gross capital stocks in $t > 0$, we add the net investment measured as the difference in tangible assets.

$$Gross\_capital\_stock_t = Gross\_capital\_stock_{t-1} + tang\_assets_t - tang\_assets_{t-1}$$

All investment and gross capital stocks are deflated using the GDP deflator for gross fixed capital formation.

Labor share We assume Cobb-Douglas production function with constant returns to scale for all firms, where $Y = AK^{(1-\alpha_L)}L^{\alpha_L}$. Labor share α_L is calculated for each 2-digit industry as the share of total wage bills to total value added.

TFP measurement, conventional Based on the value added, gross capital stock, and labour share, measured TFP is a residual calculated as in the following:

$$\log \hat{A}_{i,t} = \log(value\_added)_{i,t} - \alpha_{Lj,t} \log(L)_{i,t} - (1 - \alpha_{Lj,t}) \log(gross\_capital\_stock)_{i,t} \tag{14}$$

where j is the two-digit industry code that firm i belongs to.

TFP measurement, including intangible capital We follow the same method as in the conventional measure, except that we substitute gross capital stock with the sum of gross (tangible) capital stock and intangible capital, which is denoted as total capital stock.

$$\log \hat{A}_{i,t} = \log(value\_added)_{i,t} - \alpha_{Lj,t} \log(L)_{i,t} - (1 - \alpha_{Lj,t}) \log(total.capital.stock)_{i,t} \tag{15}$$

where j is the two-digit industry code that firm i belongs to.

B.2 Empirical analysis using conventional TFP

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.

Table 9: Shadow financing, intangibles, and productivity

VARIABLES	(1) $frac.shadow_t$	(2) $frac.shadow_t$	(3) $frac.shadow_t$
TFP_t	0.0204***	0.0206***	-0.000469
	(0.00565)	(0.00565)	(0.00536)
$intang.intensity_t$	0.261***	0.220***	0.118
	(0.0400)	(0.0436)	(0.0898)
$ln\ tot.cap_t$	-0.0209***	-0.0209***	-0.0828***
	(0.00555)	(0.00555)	(0.0267)
$post.reform_t$	0.0778***	0.0466***	0.0138
	(0.00716)	(0.0132)	(0.0118)
$intang.intensity_t$		0.0740**	0.160***
$\times\ post.reform_t$		(0.0293)	(0.0265)
Observations	8,863	8,863	8,733
Fixed effecs	None	None	Firm
R2	0.0991	0.0997	0.765

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Data There are two major 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.[13] We also use average yields on AA- and BBB- rated corporate 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).[14]

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:

[13]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.

[14]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.

- 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 24 summarizes the loan interest rate distributions for months December 2013 and December 2018.

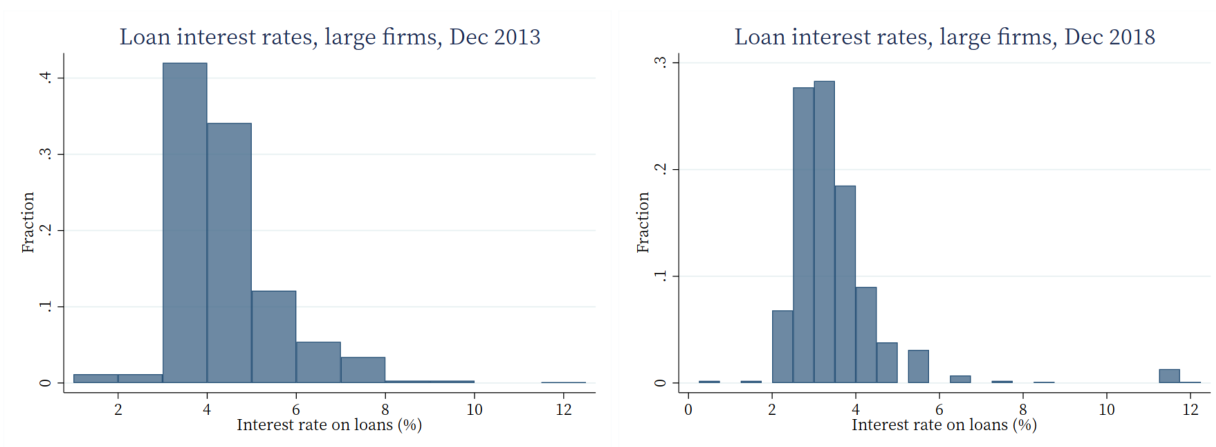

Figure 24: Interest rates to large corporations by banks, December 2013 and 2018

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.

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 25 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 25, three non-bank lenders' interest rates are depicted, in addition to the bank loan rates for large corporations and bond yields of BBB- 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.

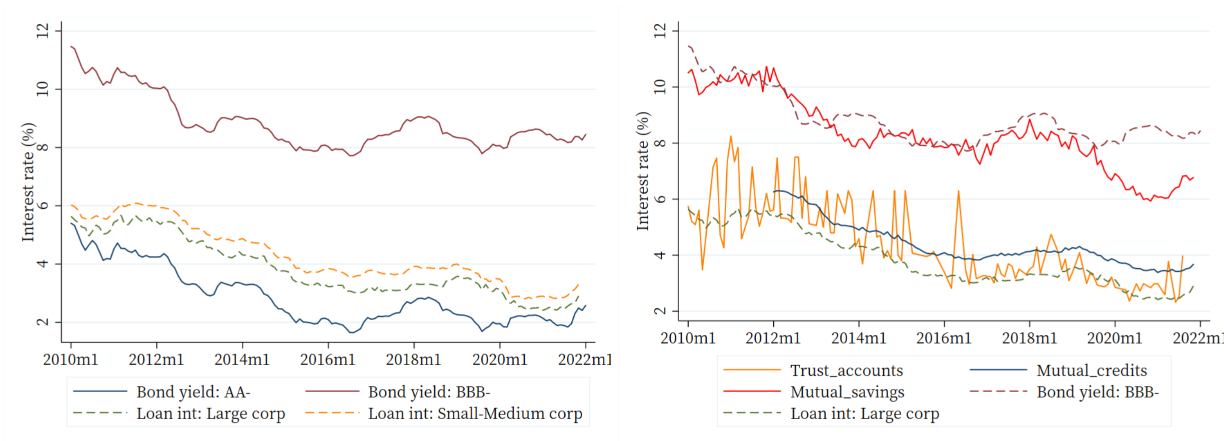

Figure 25: Interest rates to corporations by types of borrowing

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

Effective interest rates at firm level Figure 26 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.

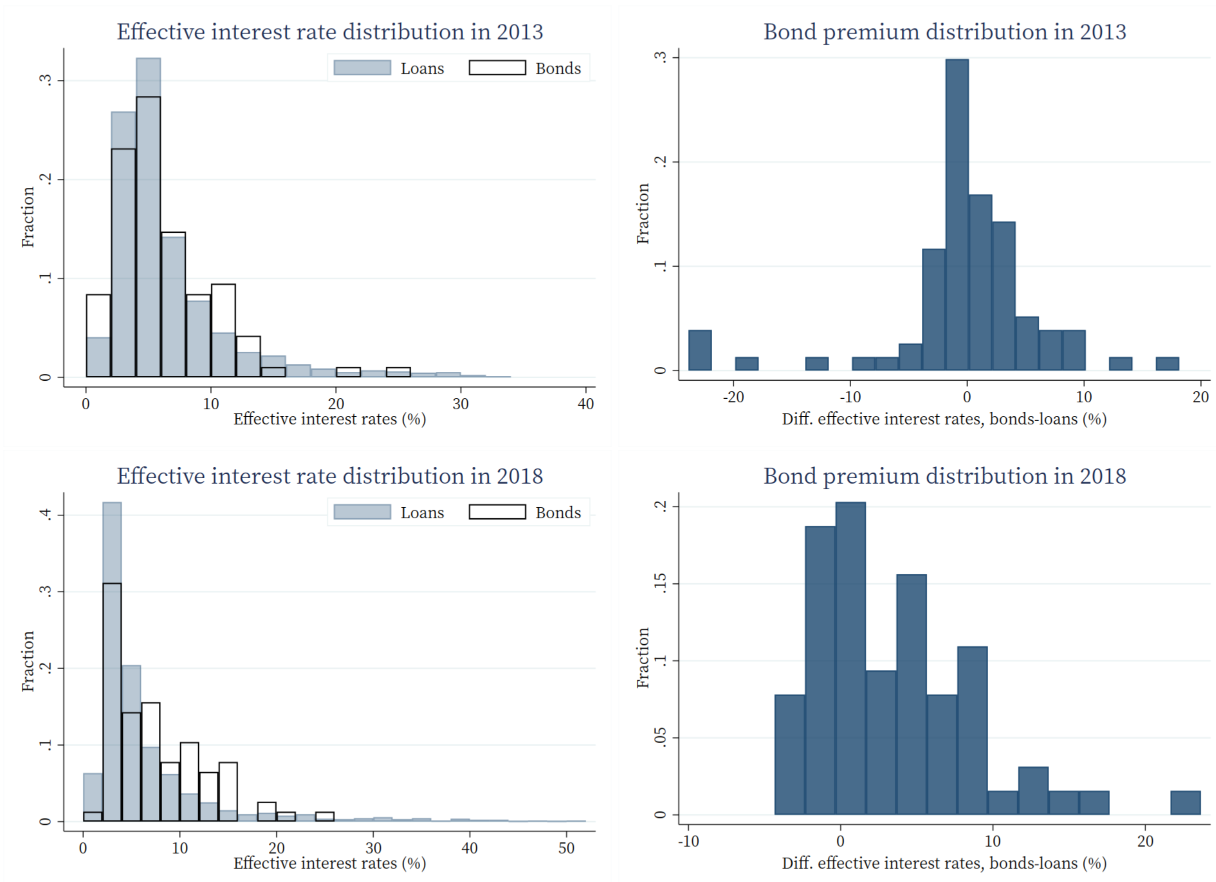

Figure 26: Effective interest rates and bond premium distribution, 2013 and 2018

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