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Strapped for Cash: The Role of Financial Constraints for Innovating Firms

Abstract

This paper makes use of a reform that allowed firms to use patents as stand-alone collateral, to estimate the magnitude of collateral constraints and to quantify the aggregate impact of these constraints on misallocation and productivity. Using matched firm-bank data for Norway, we find that bank borrowing increased for firms affected by the reform relative to the control group. We also find an increase in the capital stock, employment and innovation as well as equity funding. We interpret the results through the lens of a model of monopolistic competition with potentially collateral constrained heterogeneous firms. Parameterizing the model using well-identified moments from the reduced form exercise, we find quantitatively large gains in output per worker in the sectors in the economy dominated by constrained (and intangible-intensive) firms. The gains are primarily driven by capital deepening, whereas within-industry misallocation plays a smaller role.

JEL-Codes: D250, G320, L250, L260, O340, O470.

Keywords: intangible capital, patents, credit constraints, misallocation, productivity.

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1 Introduction

Investments in intangibles are becoming increasingly important. Since the turn of the century, firms in developed economies invest more in intangible assets, like R&D and software, than tangible assets (Haskel and Westlake, 2017, Corrado and Hulten, 2010). Yet firms that are intensive in intangible capital may struggle to get access to bank credit. The literature has pointed to at least two reasons for this: First, due to the nature of intangible capital, substantial information asymmetries are likely to exist between firms and potential investors. Second, intangible intensive firms often have limited collateral value, which may limit their access to bank loans. These issues are particularly salient for young firms, and have become even more of a drawback after the financial crisis, as banks have come under stricter regulation regarding the riskiness of their portfolio. Bank debt is important in all stages of the life-cycle of firms: According to a recent ECB survey, bank-related products are the most relevant financing source for euro area SMEs.[1] There is also widespread use of bank debt to finance technology start-ups, also in early stages of their development (Hochberg et al., 2018). Even for listed firms, shareholders of innovative firms have strong incentives to use patent-backed debt rather than new share issues, as it avoids dilution of capital and has a leverage multiplier effect on their return on equity (Amable et al., 2010).

This paper aims to close the gap between the literature on the firm-level effects of credit constraints and the literature on the aggregate effects of financial constrains and misallocation. We make use of a reform that allowed firms to use patents as stand-alone collateral and estimate the impact of improved access to intangible collateral on firms' bank borrowing and a range of other firm outcomes related to performance, equity funding and innovation. This enables us to assess whether intangible-intensive firms in fact are collateral constrained relative to other firms and to quantify the aggregate impact of these constraints on misallocation and productivity.

In the first part of the paper, we analyze the impact on firms of a collateral reform in 2015. Internationally, patents are frequently used as collateral (see e.g. Mann, 2018). Yet, according to Norwegian law, patents could not be used as stand-alone collateral before 2015. The 2015 reform changed this, allowing firms with a patent portfolio to use those patents as stand-alone collateral. The firm-level analysis relies on an unusually rich panel data set for Norwegian firms. The data set includes details on firms' patenting activity, their bank loans, interest payments, equity funding and shareholders, along with income statement and balance sheet information, and covers the universe of firms in the economy.

[1] Survey on the access to finance of enterprises (SAFE), 2019. https://www.ecb.europa.eu/stats/ecb_surveys/safe/html/ecb.safe201905~082335a4d1.en.html#toc7

We use the reform as a quasi-natural experiment and compare the change in outcomes for firms with an initial patent portfolio (before 2015) to firms without a patent portfolio, but with similar observable initial characteristics, such as intangible-intensity. We examine the impact of the reform on firms' bank borrowing, the interest rate on their debt and number of bank connections. Due to our rich data, we are not only able to investigate the direct consequences of the reform for debt financing, but we are also able to examine the effect on (i) firm performance (e.g., the capital stock), (ii) innovation, and (iii) equity funding.

Economic theory predicts that if a firm's bank borrowing increases, while the capital stock remains the same, then the marginal product of capital is unchanged and consequently the firm is not financially constrained. In this case, the firm may simply be substituting between bank debt and other sources of funding. However, if a treated firm increases its borrowing and invests in (physical or intangible) capital so that the marginal revenue product of capital (MRPK) declines, then this suggests that the firm is ex ante financially constrained. Therefore, having information on both bank borrowing and other firm outcomes is key to determine the magnitude of collateral constraints.

Our results show that improved access to intangible collateral led to increased bank borrowing for treated firms relative to the control group. At the same time, their interest rate remained unchanged while their capital stock increased and MRPK declined, suggesting that treated firms were collateral constrained. We also find a positive effect on employment and innovation, as well as on equity funding for young firms. Therefore, our results suggest that policies aiming to improve the pledgeability of intangible assets, such as patents, can alleviate financial constraints for innovating firms, and thereby contribute to innovation and economic growth.

In the second part of the paper, we analyze the impact on industry and aggregate reallocation and productivity. A drawback with the reduced-form approach is that firms in the control group will also be affected by the reform, due to general equilibrium effects. Therefore, this approach cannot be used to analyze aggregate adjustments. To tackle this, we develop a model of monopolistic competition with potentially credit constrained heterogeneous firms, in the spirit of Hsieh and Klenow (2009) and Melitz (2003). We show that removing credit constraints increases output per worker through reduced misallocation and capital deepening: Removing the friction leads to equalization of the marginal product of capital across firms, which reduces misallocation in the economy and raises output per worker. In addition, if the aggregate supply of capital is elastic, then constrained firms will invest more and become more capital intensive, without completely crowding out capital from unconstrained firms. The increase in aggregate capital will also raise output per worker.

We show that there is a simple mapping between the reduced-form estimates and the model primitives, which allows us to quantify the aggregate economic impact of the collateral reform. Specifically, the reduction in the capital friction can be computed based on the difference-in-differences estimates from the reduced form analysis along with observed values for firms' pre-reform capital share, firms' market share and the elasticity of substitution. Importantly, our methodology sidesteps many of the challenges in the traditional misallocation literature, such as the measurement error and estimation of revenue total factor productivity (TFPR). While our results are specific to our context, we believe this methodology can be useful for analyzing a wide range of economic questions, in a parsimonious and transparent framework.

Our quantitative results indicate that the removal of the collateral constraint increased labor productivity. Industry output per worker increased by up to three percent, and were concentrated in sectors of the economy dominated by innovative and credit constrained firms. The economic magnitude of the gains are substantial and they are primarily driven by capital deepening, whereas within-industry misallocation plays a smaller role.

The paper makes contributions to three distinct areas of research. First, we contribute to the general literature on the firm-level effects of credit constraints. Amiti and Weinstein (2011), Paravisini et al. (2015) and Zia (2008) analyze the role of financial shocks on exports. Banerjee and Duflo (2014) and Rotemberg (2019) analyze the impact of a directed lending program in India. Compared to this literature, we provide evidence on a specific constraint - the pledgeability of collateral - which might be especially binding for intangible- and innovation-intensive firms.

Second, the paper contributes to the literature on the role of intangible assets in corporate finance. Falato et al. (2022) show the importance of intangible assets in explaining the upward trend in US corporate cash holdings. Brown et al. (2009) estimate a dynamic R&D model and find that financial constraints play an important role in the financing of R&D for young firms in the US. Amable et al. (2010) build an endogenous growth model to show how the assignment of patents as collateral can help an economy achieve high growth rates of innovations, despite financial constraints. Mann (2018) studies the impact on debt and innovation when creditor rights to patents are strengthened. Hochberg et al. (2018) analyze the impact on firms' debt of thicker trading in the secondary market for patents. Chava et al. (2017) show that an increase in the value of borrowers' patents, either through greater patent protection or creditor rights over collateral, results in cheaper loans. Farre-Mensa et al. (2020) show that getting a patent granted increases sales and the chances of securing a loan by pledging the patent as collateral.[2] Compared to this line of research, our paper not only estimates the effect of improved pledgeability, but also quantifies the aggregate

[2]See also Hall (2019) for a recent literature review.

implications on misallocation and growth. Moreover, we do not only address the impact of reduced credit constraints on access to debt, but also investigate potential complementarities related to firm growth, innovation and equity funding.[3] Finally, while the previous literature has used data on publicly listed firms, or a subset of firms in the economy, our analysis covers the universe of firms in the economy and thus also startups, which are known to play an important role in driving innovation.

Third, we contribute to the literature on financial constrains and misallocation, see e.g. Bau and Matray (forthcoming), Buera et al. (2011), Gopinath et al. (2017), Hsieh and Klenow (2009), Karabarbounis and Macnamara (2021), Midrigan and Xu (2014) and Moll (2014), and intangibles and misallocation, see e.g. Chiavari and Goraya (2022), Lehr (2022) and De Ridder (2022).[4] To our knowledge, this is the first paper to focus on the impact of collateral constraints related to intangible assets on misallocation. From a methodological point of view, our analysis of misallocation differs from previous studies, as we provide a simple mapping from well-identified reduced form estimates to the quantification of a theoretical model.[5]

The remainder of this paper is organized as follows. Section 2 documents the 2015 reform and discusses testable predictions using a simple economic framework. Section 3 presents the data and describes how we compute key variables. Section 4 presents the empirical model and results. Section 5 develops a framework that allows us to quantify the aggregate impact of reduced financial constraints on resource allocation, employment and growth. Section 6 provides some concluding remarks.

2 Background and Testable Predictions

2.1 Background

The empirical analysis relies on a reform to the law on collateral in Norway. The reform improved the pledgeability of patents by allowing firms to use patents as stand-alone collateral.[6] The reform came into force on July 1st 2015, less than 6 months after the details were announced. Prior to this, a patent could only be used as collateral (i) in conjunction with a physical asset ("driftstilbehøret") and/or (ii) if the patent is utilized in current production.

[3]In a related paper, Altomonte et al. (2022) focus on the role of intangible assets in driving differences in mark-ups across firms, and use liquidity shocks to instrument for investments in intangible assets.

[4]Restuccia and Rogerson (2017) provide a survey of the misallocation literature.

[5]In contemporaneous work focusing on exporting, Finlay (2021) parameterizes a model of misallocation using a directed credit policy towards selected industrial sectors in India as a source of exogenous variation.

[6]The use of collateral is regulated by law. For details on the law, see https://lovdata.no/dokument/NL/lov/1980-02-08-2#KAPITTEL_4-2.

Therefore, a firm without a revenue flow coming from the patent itself could not use the patent as collateral.

The reform was introduced precisely to alleviate financial constraints for the growing number of innovative and intangible-intensive firms, and was not part of a bigger and comprehensive reform. According to a report by The International Association for the Protection of Intellectual Property (AIPPI) the majority of developed countries does by now allow for the use of patents as collateral.[7] Compared to other countries, the reform in Norway came relatively late. Already by 2013, 38% of U.S. patenting firms had previously pledged patents as collateral (Mann, 2018).

2.2 Testable Predictions

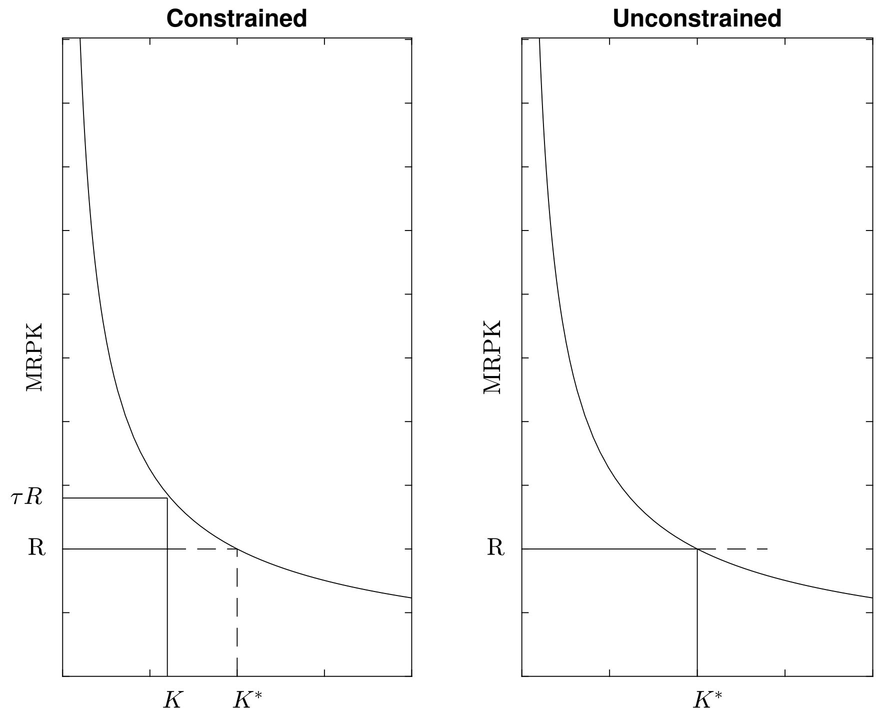
In this section, we present a simple economic framework for analyzing the impact of the 2015 collateral reform on firm outcomes. Importantly, we develop predictions that will help identify whether firms are credit constrained or not.

Consider a firm with a production function $Y_{si} = f\left(K_{si}, L_{si}\right)$, where K_{si} is capital and L_{si} is labor, and the subscripts i and s denote the firm and sector, respectively. K_{si} is financed by short- and long-term loans and equity. The firm is maximizing profits, is a price-taker in capital and labor markets and faces an interest rate R. It follows that the optimal level of capital, K^*_{si}, is such that the marginal revenue product of capital equals the interest rate, $MRPK_{si} = R$. We follow Banerjee and Duflo (2014) and define firms as constrained if they have less capital than the amount they would want at the interest rate that they are currently paying. Therefore, the firm is constrained if the optimal amount is greater than the actual amount, $K^*_{si} > K_{si}$.

We model the 2015 reform as an increase in total available funding for those firms that can pledge patents as collateral. It follows from the firm's maximization problem that the capital stock remains unchanged for unconstrained firms, but that it increases for constrained firms. Figure 1 illustrates the allocation pre- to post-reform. The downward sloping line is the $MRPK_{si}$ curve as a function of the capital stock. The left figure plots the situation for a constrained firm. Prior to the reform, the capital stock is $K_{si} < K^*_{si}$ and $MRPK_{si} = \tau R > R$, where τ is the implicit capital friction. Post reform, total available funding has increased so that the firm is no longer constrained, i.e. $K_{si} = K^*_{si}$ and $MRPK_{si}$ has declined from τR to R. The right figure plots the situation for an unconstrained firm. Pre reform, the capital stock is already at K^*_{si}. An increase in total funding will therefore have no impact on the capital stock or on $MPRK_{si}$.

[7] https://aippi.soutron.net/Portal/DownloadImageFile.ashx?fieldValueId=1188

Figure 1: Impact of the collateral reform on constrained and unconstrained firms



According to our framework, credit constrained firms will increase their borrowing and capital stock, while $MPRK_{si}$ will decline. If we only observe an increase in borrowing, but no change in the capital stock, then this may simply reflect that firms are substituting from other sources of funding, e.g. from equity to bank loans.

3 Data and Descriptives

Our empirical analysis is based on five data sets. The first data set is administrative firm register data from Statistics Norway. The data set covers the universe of firms across all sectors. The register data provides information on the date of the entry and exit of each individual firm, allowing us to calculate the firm's age. The register also holds data on firms' number of employees.

The second data set is income statement and balance sheet data from Statistics Norway for all private non-financial joint-stock companies.[8] The income statement and balance sheet data is based on data from annual reports that according to Norwegian law must be filed with the public Register of Company Accounts. The accounting data is unusually rich and detailed, and importantly for our purposes, we can differentiate between actual intangible assets, such as R&D, patents, and goodwill, and deferred tax assets.

[8] 85 percent of Norwegian firms with one or more employees are joint-stock firms.

The third data set is bank lending data from the Norwegian Tax Authority. We have annual data on all loans given by financial institutions registered in Norway to Norwegian firms. The unit of observation is a loan-firm-bank-year. For each observation, we observe the value of the loan (end year) and interest payments accumulated over the year.

The fourth data set contains shareholder information by firm. We have information by shareholder, firm and year, which allows us to compute the number of shareholders, the value of the issue of new equity, and whether there is a change in the composition of shareholders.

The fifth data set is based on the universe of published patent applications submitted to the Norwegian Patent Office. For each patent application we have detailed information including the year of filing and identity of the applicant (patentee), i.e. the firm or person responsible for the application.

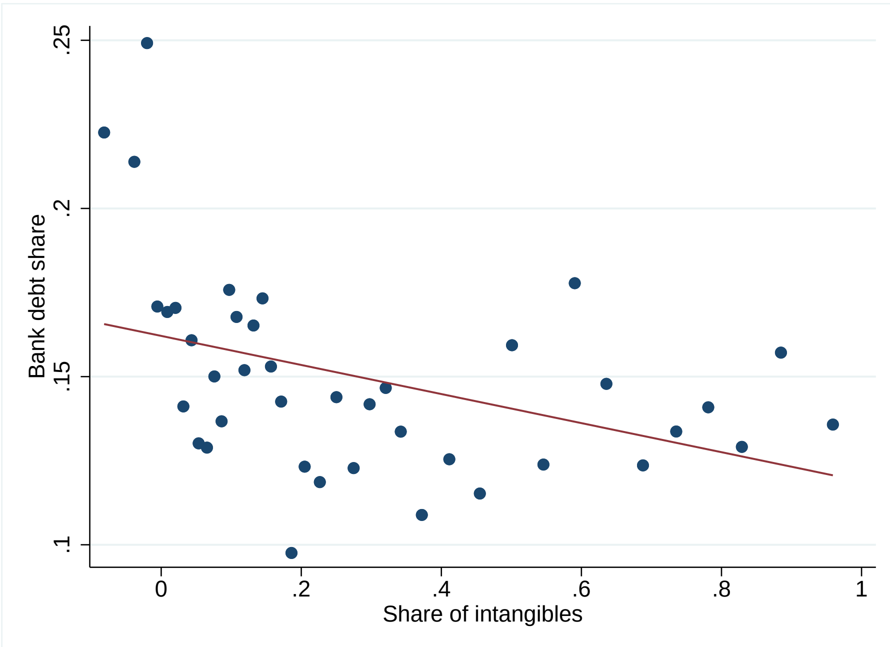
We link all data sets with a unique firm identifier. Our sample is constructed to cover the years 2005 to 2018. We let 2010 to 2015 define the pre-shock period and 2015 to 2018 define the post-shock period. We use the period 2005-2010 for falsification tests.

We end this section by documenting the relationship between bank borrowing and intangible assets. Bank borrowing is measured as bank debt relative to sales. We measure the share of intangibles in a firm's total fixed assets as the value of the sum of R&D, patents, licenses, trademarks and goodwill divided by the value of all fixed assets. Figure 2 shows a binned scatter plot between firms' share of intangibles and bank debt share. Firms are grouped into equal-sized bins according to their share of intangibles, and the scatter plot shows the mean of the share of intangibles and bank debt within each bin, controlling for industry fixed effects (NACE 2-digit). We observe that the higher the share of intangibles, the lower the bank debt share. Our findings may indicate that intangible intensive firms are credit constrained as compared to other firms (see e.g. Hall, 2010).

4 Empirical Analysis

In this section, we present the identification strategy and reduced-form results. By using the testable predictions from Section 2, we provide firm-level empirical evidence on the effects of improved access to intangible collateral on firm level outcomes. First, we investigate the direct effect on external financing. Second, we exploit our rich data to examine the indirect effects on firm performance, innovation and access to equity funding.

Figure 2: Bank Debt Share and Share of Intangibles



Note: Data from 2010. Bank debt share is calculated as bank debt relative to sales. Share of intangibles is calculated as value of the sum of R&D, patents, licenses, trademarks and goodwill, as reported in the balance sheet, divided by the total value of fixed assets. The scatter plot shows the mean of the share of intangibles and bank debt within each bin, controlling for industry fixed effects (NACE 2-digit).

4.1 Empirical Model

In order to identify the impact of improved access to external financing we use a difference-in-difference model. In the baseline specification, we compare firms with an ex-ante patent portfolio to similar firms without a patent portfolio. The treatment group consists of firms with at least one patent application in the five years prior to the reform.[9] The baseline specification is given by

$$y_{it} = \alpha_i + \beta P_i \times Post_t + \gamma X_{i0} \times \delta_t + \delta_{st} + \varepsilon_{it}, \tag{1}$$

where y_{it} is the outcome variable, the variable P_i takes on the value one if firm i had at least one patent application between 2010 and 2015, and zero otherwise, and the dummy $Post_t$ takes on the value one for years later than 2015. We also include firm fixed effects, α_i, and industry-year fixed effects (NACE 2-digit), δ_{st}. We also aim to account for trends that are related to firm characteristics such as firm size, firm assets and cash flow. We do so by including a set of control variables, X_{i0}, which are computed based on the first year the firm is observed after 2010, interacted with year dummies δ_t. The control variables are: log employment, log value of fixed tangible assets, the share of intangibles in total fixed assets (intangible-intensity), a dummy for whether or not the firm has positive EBITDA, and a dummy for whether the firm has received public funding through a government agency.

Intuitively, we compare outcomes pre- to post-reform, for two firms that have the same observable characteristics, but that differ according to their assignment to treatment and control group. Importantly, we compare firms within the same industry and with similar size and intangible-intensity.

We consider a set of outcome variables reflecting firms' access to funding, funding structure and financing costs: (i) a bank debt dummy, which takes on the value one if the firm has bank debt; (ii) log of the value of bank debt; (iii) the ratio of bank debt relative to total sales; (iv) the ratio of short term debt to total debt; (v) number of bank connections; and (vi) the interest rate on bank debt. The number of bank connections is calculated based on the firm-bank data. The interest rate on bank debt is also constructed using the firm-bank data: we calculate the interest rate as total interest payments during the year t relative to the average bank debt across year t and $t-1$.

In the subsequent sections, we investigate the impact on firms' performance: sales, employment, capital stock (measured as total fixed assets) and the marginal revenue product of capital (MRPK), equity funding and innovation.

[9] According to the 2015 law, the following may be used as collateral: Granted patents, patent applications to the Norwegian Patent Office, international patent applications and European patent applications.

4.2 Empirical Results on External Financing

We estimate the empirical model, see equation (1), and report the results on a set of different measures of external financing in Table 1. Column (1) reports the results on bank debt, where the outcome is a binary variable indicating whether the firm has a bank loan or not. The results show a five percentage point increase in the likelihood of bank borrowing for the treatment relative to the control group. Column (2) uses the log of bank debt as the outcome variable. The point estimate is insignificant and close to zero. Column (3) uses bank debt relative to sales, which captures adjustments both at the extensive and intensive margin. The results show a 1.5 percentage point increase in the bank debt share. Column (4) measures short term debt relative to total debt as reported in the balance sheet data. Short term debt declines by 2.7 percentage points, suggesting that less secure short term debt is converted to long-term debt backed by collateral. The results in column (5) show that the number of bank connections increased, suggesting that treated firms obtained more lines of credit after the reform. Finally, column (6) reports results for the firm-specific interest rate. We find no significant change in the interest rate. In sum, the results suggest that improved availability of collateral led to more bank borrowing, changes in the funding structure as well as more bank connections, while the price of credit was not affected.

Table 1: Credit Access

	Bank loan dummy (1)	Log bank debt (2)	$\frac{Bank\ Debt}{Total\ Sales}$ (3)	$\frac{Short\ Debt}{Total\ Debt}$ (4)	No of Banks (5)	Interest rate (6)
$Post_t \times P_i$	0.051**	-0.017	0.016**	-0.027**	0.144***	0.003
	(0.021)	(0.202)	(0.007)	(0.011)	(0.046)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	726,550	330,952	697,296	724,261	726,550	334,105

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, a dummy for positive EBITDA, and a dummy for public funding, all interacted with year dummies. $^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Heterogeneity We also explore heterogeneous responses to improved access to intangible collateral. In particular we focus on young firms. We do so by including an extra interaction between $Post_t \times P_i$ and $Young_i$, where $Young_i = 1$ if a firm is six years or younger in 2015. To make sure that any potential results are not driven by young firms being on a different trend compared to older firms, we also include an interaction term between $Young_i$ and year dummies. The results are reported in Table 2. The triple interaction term is mostly insignificant, suggesting that there are no differential effects by firm age. One exception is short term debt, where the reduction in short debt relative to total debt appears to be driven by young firms.

Table 2: Credit Access – Young Firms

	Bank loan dummy (1)	Log bank debt (2)	$\frac{Bank\ Debt}{Total\ Sales}$ (3)	$\frac{Short\ Debt}{Total\ Debt}$ (4)	No of Banks (5)	Interest rate (6)
$Post_t \times P_i$	0.045**	-0.040	0.013*	-0.014	0.144***	0.004
	(0.023)	(0.213)	(0.007)	(0.011)	(0.050)	(0.004)
$Post_t \times P_i \times Young_i$	0.071	0.357	0.030	-0.114***	.049	-0.001
	(0.062)	(0.624)	(0.023)	(0.037)	(0.133)	(0.009)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Young*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	726,550	330,952	697,296	724,261	726,550	334,105

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. $Young_i = 1$ if a firm is 6 years or younger in 2015.Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, a dummy for positive EBITDA, and a dummy for public funding, all interacted with year dummies. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

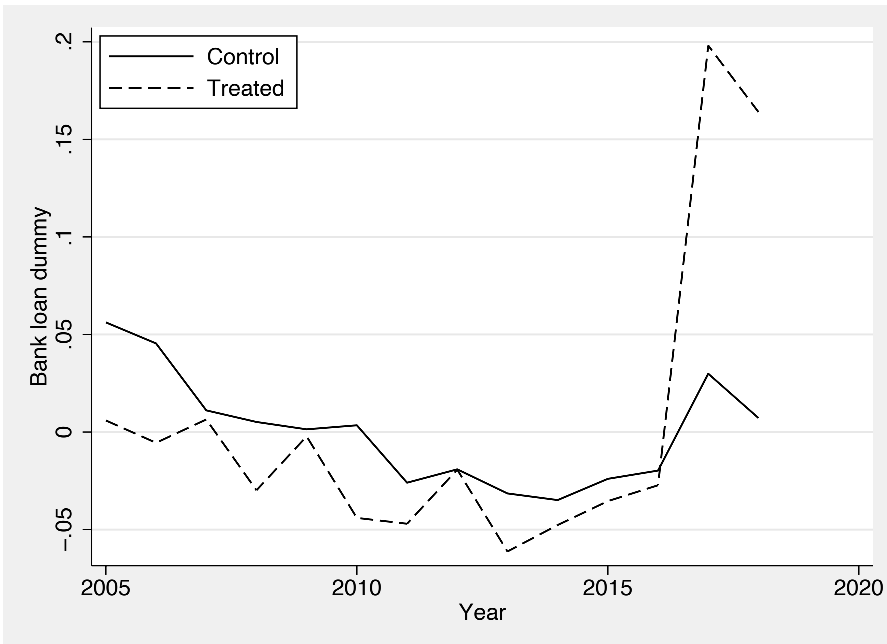
4.3 Pre-trends

Identification of the treatment effect requires similar pre-trends for treated and control firms. We investigate this in three different ways: First, we plot pre-trends for a key outcome variable, the bank loan dummy. Figure 3 shows the mean of the variable for the treatment and control groups, after residualizing the variable on all controls and fixed effects. The pre-trends are overall relatively similar for the two groups.

Second, we estimate equation (1) for the period 2005 to 2015 and use 2010 as the treatment year, i.e. the variable P_i now takes on the value one if firm i had at least one patent application between 2005 and 2010, and zero otherwise, while the dummy $Post_t$ takes on the value one for years later than 2010. The results are reported in Table 3. The point estimates are close to zero and insignificant for most measures of credit access, suggesting that the treatment and control groups are not inherently on differential trends.

Third, we define the treatment group in the same way as in the baseline, i.e. the variable P_i takes on the value one if firm i had at least one patent application between 2010 and 2015. But rather than comparing the outcomes pre- and post the reform, we compare the outcomes prior to 2010 with outcomes in the five year period before the reform, 2010-2015. The results reported in Table 4 shows that differential pre-trends are absent.

Figure 3: Pre-trends: Bank Debt dummy



Note: The figure shows the average of the bank loan dummy after residualizing the variable on all controls and fixed effects, for the treatment and control groups.

Table 3: Credit Access - Placebo

	Bank loan dummy (1)	Log bank debt (2)	$\frac{Bank\ Debt}{Total\ Sales}$ (3)	$\frac{Short\ Debt}{Total\ Debt}$ (4)	No of Banks (5)	Interest rate (6)
$Post2010 \times P_i$	-0.003	0.095	0.007	–0.025*	-0.010	-0.009***
	(0.018)	(0.165)	(0.006)	(0.014)	(0.035)	(0.0043)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	842,871	399,059	801,206	841,573	842,871	407,491

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2005 to 2015. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, a dummy for positive EBITDA, and a dummy for public funding, all interacted with year dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Credit Access - Placebo. Identical population as in baseline.

	Bank loan dummy (1)	Log bank debt (2)	$\frac{Bank\ Debt}{Total\ Sales}$ (3)	$\frac{Short\ Debt}{Total\ Debt}$ (4)	No of Banks (5)	Interest rate (6)
$Pre2010 \times P_i$	-0.018	-0.017	-0.005	0.010	-0.033	0.007*
	(0.022)	(0.175)	(0.007)	(0.014)	(0.040)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	842,871	399,059	801,259	841,573	842,871	407,491

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2005 to 2015. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, a dummy for positive EBITDA, and a dummy for public funding, all interacted with year dummies. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4.4 Empirical Results on Firm Performance

Next, we turn to empirical results on firm performance. Table 5 reports results for the outcome variables: employment, sales, capital, measured as total fixed assets (all in logs), and marginal revenue product of capital (MRPK).[10] MRPK is calculated as the inverse of

[10] Firms face different accounting rules depending on firm size. They may therefore value assets differently. In the regression with capital stock as an outcome, we add an extra control variable that indicates which accounting rules are used.

the capital to sales ratio, a commonly used measure under the assumption of a Cobb-Douglas production function.

We find that employment increased by roughly .05 log points (column (1)) and that the capital stock increased by .20 log points (column (2)), for the treatment relative to the control group. The results suggest that the reform to collateral promoted both hiring and investment among the treated firms. We find no increase in sales (column (3)). This might reflect the fact that there is a lag between investment and sales (recall that the post reform sample period is only 2015-2018). We find a significant negative effect on MRPK for treated firms (column (4)).

Table 5: Firm Performance

	Log employment (1)	Log capital (2)	Log sales (3)	MRPK (4)
$Post_t \times P_i$	0.051**	0.200***	-0.004	-0.224***
	(0.030)	(0.065)	(0.042)	(0.057)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes
Observations	726,550	671,108	717,848	640,868

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. MRPK is measured by operating income divided by total fixed assets. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in fixed assets, and a dummy for public funding, all interacted with year dummies. With capital stock as outcome we add an extra control variable to account for different accounting rules. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Section 2 discussed testable predictions for firms with collateral constraints. The sufficient and necessary conditions for a firm to be collateral constrained is that in the aftermath of the reform (i) bank borrowing increases, (ii) the capital stock increases and (iii) MRPK declines. Our empirical results are consistent with all three predictions. Therefore, our results support the hypothesis that the reform relaxed financial constraints for the firms in the treatment group.

Heterogeneity Turning to heterogeneous responses with respect to firm performance, we proceed as above and report the results in Table 6. We find stronger effects for young firms for employment, but not for sales, capital stock and MRPK.

Table 6: Firm Performance – Young Firms

	Log employment (1)	Log sales (2)	Log capital (3)	MRPK (4)
$Post_t \times P_i$	0.036	-0.0274	0.164**	-0.205***
	(0.032)	(0.041)	(0.067)	(0.057)
$Post_t \times P_i \times Young_i$	0.181**	0.258	0.359	-0.112*
	(0.092)	(0.158)	(0.226)	(0.221)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes
Young*year FE	Yes	Yes	Yes	Yes
Observations	726,550	717,848	671,108	640,868

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. $Young_i = 1$ if a firm is 6 years or younger in 2015. Capital is measured by total fixed tangible assets. MRPK is measured by operating income divided by total fixed assets. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in fixed assets, and a dummy for public funding, all interacted with year dummies. With capital stock as outcome we add an extra control variable to account for different accounting rules. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.5 Empirical Results on Equity Funding

This section investigates the impact improved access to intangible collateral on equity funding. Reduced borrowing constraints may allow firms to increase their investments, which in turn improve their profitability and returns to equity, attracting more investment and new investors. New bank loans may also serve as a signal that alleviates asymmetric information hindering the financing of these firms and that improves investors' assessment of the treatment firms.

To investigate the impact on equity funding, we re-estimate our baseline model. In columns (1) and (2) in Table 7, we report the results when the outcome variable is an indicator variable for whether the firm has issued new equity. We do not find any effect on new equity in general, but when we account for age heterogeneity, we find a positive effect for young firms. In columns (3) and (4) in Table 7, we consider the impact on number of shareholders. Again we do not find an average effect, but we observe a positive effect on number of shareholders among young firms.

Table 7: Equity Funding

	Equity issue dummy (1)	Equity issue dummy (2)	Log number of shareholders (3)	Log number of shareholders (4)
$Post_t \times P_i$	0.017	-0.007	-0.058	-0.085**
	(0.015)	(0.015)	(0.040)	(0.042)
$Post_t \times P_i \times Young$		0.137***		0.225*
		(0.050)		(0.123)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes
Young firm*Year FE	No	Yes	No	Yes
Observations	638,897	638,897	638,894	638,894

Note: Standard errors in parenthesis are clustered on firm. The Equity issue dummy takes on the value one if the firm issues new stock, and zero otherwise. $Young_i = 1$ if a firm is 6 years or younger in 2015. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in fixed assets, and a dummy for public funding, all interacted with year dummies. $^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

4.6 Empirical Results on Innovation

Finally, we investigate whether the reform had an impact on firms' innovation. We estimate the following specification on the cross-section of firms in 2015:

$$y_i = \alpha + \beta P_i + \gamma X_i + \delta_s + \varepsilon_i, \tag{2}$$

where y_{it} is a measure of post-reform innovation, and the variable P_i is identical to the analysis above. We include industry fixed effects (NACE 2-digit), δ_s, and a set of firm specific control variables: log employment, log value of fixed tangible assets, the share of intangibles in total fixed assets, a dummy for whether on not the firm has positive EBITDA, and a dummy for whether the firm has received public funding through a government agency. We use two different measures of innovation:, a dummy that takes on the value one if the firm has a at least one patent application in the period 2016-2018, and a count of the number of patent applications filed by the firm in the period 2016-2018. We also examine whether young firms responded differently.[11]

The results are reported in Table 8. They suggest that the reform also has a benign

[11] Note that we cannot estimate equation (1) when patenting is the outcome variable, as this would create a mechanical correlation between left- and right hand side variables.

Table 8: Patenting

	Patent dummy (1)	Patent dummy (2)	Patent count (3)	Patent count (4)
P_i	0.217***	0.209***	0.936***	1.002***
	(0.022)	(0.025)	(0.211)	(0.237)
$P_i \times Young_i$		0.054		-0.469*
		(0.053)		(0.261)
Controls	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Observations	84,988	84,988	75,330	75,330

Note: Standard errors in parenthesis are clustered on firm. The patent dummy takes on the value one if the firm has filed patent applications in the period 2016-2018, and zero otherwise. The patent count variable is a count of patent applications in the period 2016 to 2018. $Young_i = 1$ if a firm is 6 years or younger in 2015. The Controls are firm specific and include: log employment, log fixed tangible assets, share of intangibles in fixed assets, and a dummy for public funding, all for the year 2015. $^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

impact on innovation. There is no evidence of strong heterogeneous effects across firm age.

5 The Aggregate Impact on Misallocation and Growth

We now turn to study the implications of our findings for industry and aggregate outcomes. First we present a parsimonious model of monopolistic competition and heterogeneous firms, in the spirit of Melitz (2003) and Hsieh and Klenow (2009), which we use to investigate the impact of credit constraints on sectoral and aggregate productivity. We then describe our methodology to quantify the model, and finally we present the results from the quantitative analysis. The framework allows us to study and decompose two important sources of growth; reduced misallocation and increased capital deepening.

5.1 Framework

A single final good Y is produced by representative firms in a perfectly competitive final product market. Aggregate output is produced using a Cobb-Douglas production function:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s},$$

where Y_s is output from industry s and $\sum_{s=1}^{S} \theta_s = 1$. Sectoral output is itself a CES aggregate of M_s firms producing differentiated products:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)},$$

where σ is the elasticity of substitution across firms and Y_{si} is output of firm i. We let P_s denote the corresponding sector-level CES price index. The production technology of firm i is also Cobb-Douglas:

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s},$$

where L_{si} and K_{si} are employment and capital of firm i, respectively, and α_s is the capital cost share in industry s.

Some firms may lack access to credit, or they may not have access to as much credit as they want given the interest rate r. We let $\tau_{si} \geq 1$ reflect the magnitude of credit constraints. A firm will invest in capital until its marginal revenue product of capital, $MRPK_{si}$, equals $\tau_{si} r$, where r is the interest rate. The firm's implicit cost of capital is therefore $\tau_{si} r$. Profits are then given by

$$\pi_{si} = p_{si} Y_{si} - w L_{si} - \tau_{si} r K_{si}.$$

Given these assumptions, the firm's optimal price is a constant markup over marginal costs:[12]

$$p_{si} = \kappa \frac{\sigma}{\sigma - 1} \frac{(\tau_{si} r)^{\alpha_s} w^{1-\alpha_s}}{A_{si}}.$$

5.2 Equilibrium

The model can be solved in changes following the "exact hat algebra" approach by Dekle et al. (2008). We focus on an initial equilibrium with pre-reform credit constraints τ_{si}, and a counterfactual (post-reform) equilibrium without credit constraints, $\tau_{si} = 1$ for all i, holding everything else constant.[13] The "hat" notation refers to relative changes, i.e. $\hat{x} = x'/x$, where x' is the counterfactual outcome and x is the initial outcome.

The model can be solved under two different assumptions about the capital market. The first assumption is that capital supply is infinitely elastic at interest rate r, i.e. a small open economy assumption, so that the aggregate capital stock K is endogenous and the interest rate r is exogenous. The second assumption is that aggregate capital supply is perfectly

[12] $\kappa = (\alpha_s)^{-\alpha_s} (1 - \alpha_s)^{-(1-\alpha_s)}$.

[13] I.e., the change in τ_{si} reflects the removal of credit constraints associated with the reform. We abstract from other time invariant capital and labor frictions in the economy.

inelastic and fixed at K, i.e. a closed economy assumption, so that the aggregate capital stock K is exogenous and the interest rate r is endogenous. We solve the baseline model under the first assumption, which is arguably more appropriate for a small open economy such as Norway. We solve the model under the second assumption in the Appendix Section A.3. Nominal wages are the numéraire.

Firm-level outcomes. The change in employment and the capital stock is

$$\hat{L}_{si} = \tau_{si}^{\alpha_s(\sigma-1)} \hat{P}_s^{\sigma-1}. \tag{3}$$

$$\hat{K}_{si} = \tau_{si}^{\alpha_s(\sigma-1)+1} \hat{P}_s^{\sigma-1}. \tag{4}$$

The change in labor productivity (output relative to employment) is $\hat{Y}_{si}/\hat{L}_{si} = \tau_i^{\alpha_s}$.[14] Capital, employment and labor productivity increase for the treated firms, relative to the control firms, within the same sector s. Detailed derivations are provided in Appendix Section A.

The change in the sector-level price index can be written as

$$\hat{P}_s = \left[\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{\alpha_s(\sigma-1)} \right]^{1/(1-\sigma)}, \tag{5}$$

where ω_{si} refers to the initial market share of firm i in industry s, and is calculated based on sales, i.e. $\omega_{si} = S_{si}/\sum_{i=1}^{M_s} S_{si}$. The price index, therefore, declines as credit constraints are removed. Firms with initial $\tau_{si} = 1$ will contract when frictions are removed, because they face more competition from the treated firms.

Aggregate outcomes. We follow Hsieh and Klenow (2009) and express industry output as a function of industry employment, capital and TFP:

$$Y_s = TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s}.$$

Holding industry capital and labor fixed, TFP_s is endogenous to the credit constraints in the sector. As such, TFP_s is a measure of within-industry misallocation of factors of production. In the appendix, we show that

$$\hat{K}_s = \left(\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{-1} \right)^{-1}, \tag{6}$$

and

$$T\hat{F}P_s = \left[\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{-1} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{\alpha_s(\sigma-1)} \right]^{1/(\sigma-1)}. \tag{7}$$

[14]The relative change in *sales* per worker is $\hat{S}_{si}/\hat{L}_{si} = 1$, see Appendix Section A.2.

Furthermore, industry labor productivity can be written as $\hat{Y}_s/\hat{L}_s = T\hat{F}P_s \left(\hat{K}_s/\hat{L}_s\right)^{\alpha_s}$, or simply $\hat{Y}_s/\hat{L}_s = 1/\hat{P}_s$.[15]

From equations (6) and (7) it follows that there are two distinct sources behind industry and aggregate labor productivity growth. First, labor productivity may increase because industry capital intensity increases, i.e. K_s/L_s goes up. Second, labor productivity may increase because of reduced misallocation, i.e. TFP_s rises. Below, we quantify both sources of productivity growth.

5.3 Quantification

This section describes our methodology for quantifying the model. We are interested in the industry and aggregate impact of removing the credit constraint τ_{si}. Examining the equations above, we immediately see that we only need information about four parameters: The initial friction, τ_{si}, the initial market share, ω_{si}, the elasticity of substitution, σ, and the capital cost share, α_s. By solving equation (4) with respect to τ_{si}, we can express the initial friction as a function of the growth in capital $\hat{K}_{si}$ for constrained firms (conditional on the industry price index $\hat{P}_s$). Recall that the difference-in-differences estimation in Section 4 identified the within-industry growth in capital for the treated firms. Therefore, the reduced-form estimate (see Table 5), along with information about α_s and σ, is sufficient to identify the initial friction τ_{si}. Given this estimated value for τ_{si}, we can use equation (7) to quantify the impact of removing the friction on industry misallocation. We summarize this in the following two propositions.

Proposition 1. *The credit friction is given by*

$$\tau_{si} = \left(\frac{\hat{K}_{si}}{\hat{P}_s^{\sigma-1}} \right)^{1/[\alpha_s(\sigma-1)+1]} .$$

Proposition 2. *Consider a sector production function $Y_s = TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s}$. The relative change in industry-level TFP is*

$$T\hat{F}P_s = \left[\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{-1} \right]^{\alpha_s} \left[\sum_{i=1}^{M_s} \omega_{si} \tau_{si}^{\alpha_s(\sigma-1)} \right]^{1/(\sigma-1)} .$$

Our quantitative approach has several advantages. First, the credit friction is identified from the differences-in-differences research design, and as such provides a direct estimate of

[15] Sector employment is constant, $\hat{L}_s = 1$, see Appendix Section A.

Table 9: Parameters.

β	DiD estimate, $\ln Capital_i$	0.20	
α_s	Capital share	0.30 (mean)	1 - (wage costs)/(total costs)
σ	Elasticity of substitution	4	Broda & Weinstein (2006)
ω_{si}	Sales shares		Our data, 2014.

the friction. In contrast, much of the misallocation literature relies of indirect estimates, e.g. by comparing differences in the marginal revenue product of capital between firms. Second, our framework does not rely on estimating production functions, which might introduce both measurement error and various estimation biases.

The remaining variables ω_{si}, σ and α_s are parameterized as follows. The market shares, ω_{si}, are directly observed from the balance sheet data, and refer to 2014, the year before the reform. A sector s is defined as a NACE 2-digit industry. We set the elasticity of substitution, σ, to 4, which is the mean value from Broda and Weinstein (2006).[16] The capital share, α_s, is calculated as one minus wage costs relative to total costs, where total costs include wage costs, depreciation, interest costs plus costs of equity.[17] We summarize the parameters in Table 9.

5.4 Aggregate Impact: Quantitative Results

We start by assessing the magnitude of the friction. Using *Proposition 1* along with the parameters from Table 9, we calculate the credit constraint τ_{si} for all treatment firms. Figure 4 documents the density of τ_{si} across firms.[18] For the median treated firm, $\tau_{si} = 1.12$, implying that the implicit capital cost is 12 percent higher for a median treated firm, relative to a control firm.

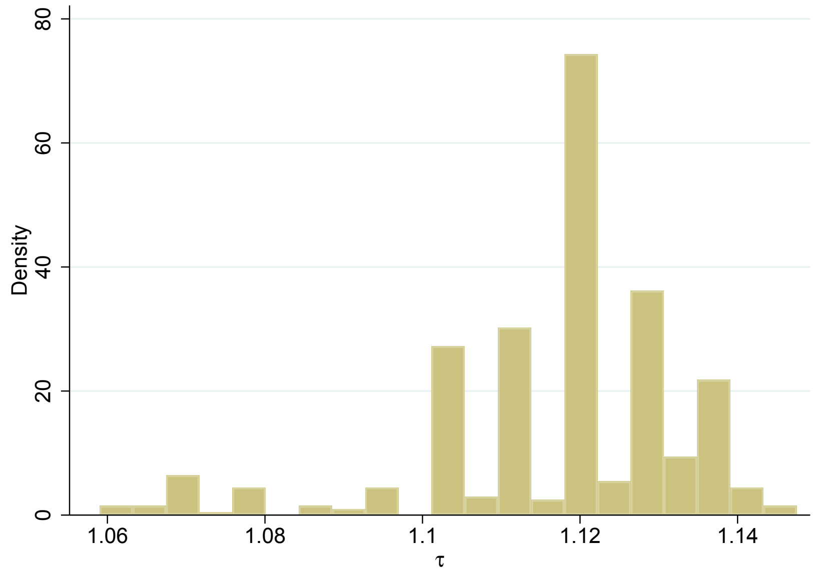
Next, we document the change in equilibrium outcomes from before to after the reform. Figure 5 shows the percentage change in employment across all firms in the economy on the vertical axis versus their initial market share on the horizontal axis. According to the model, treated firms are expanding as τ_{si} declines, whereas control group firms are contracting, as the industry price index falls. We find that both small and large firms are affected by the reform. There is no clear relationship between initial market share and subsequent employment growth. Initially, treated firms employed 6.7 percent of the workforce. After the reform, their employment share is 7.0 percent, i.e. a 0.3 percentage point increase.

[16] Three-digit goods (SITC-3), over the period 1990-2001.

[17] The costs of equity is calculated as $r \times E_i$ where E_i is equity and r is set to 0.06.

[18] The variation in τ_{si} only comes from variation across industries s, because it is only the capital share α_s that varies when applying Proposition 1.

Figure 4: Density of τ_{si}.



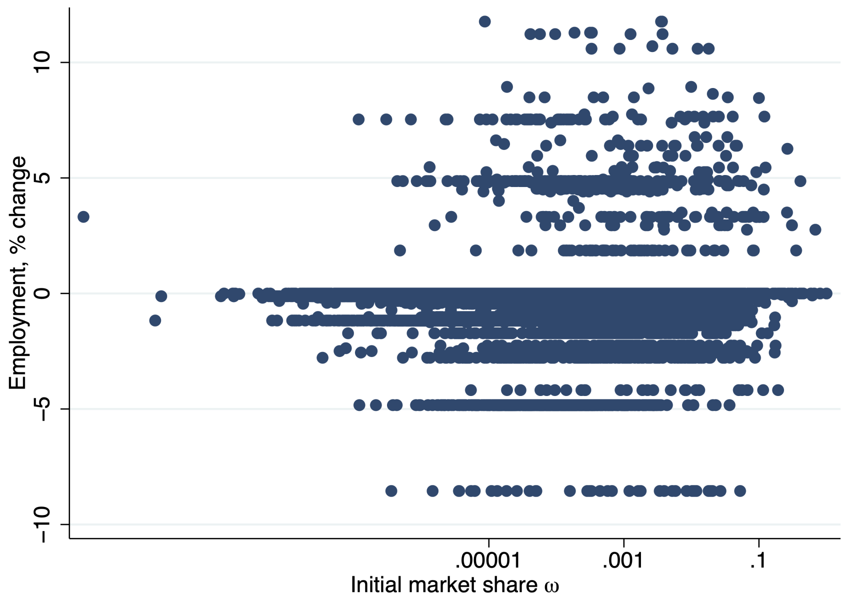
Note: The histogram shows the density of the credit constraint, τ_{si}.

Moving to the industry-level, Figure 6 documents the percentage change in output per worker by industry on the vertical axis and the industry market share of treated firms on the horizontal axis. Output per worker increases by up to three percent. Importantly, the productivity gains are concentrated in industries where treatment firms have an initially large market share, i.e. in those sectors where many firms are constrained.

Recall that industry labor productivity growth is given by $\hat{Y}_s/\hat{L}_s = T\hat{F}P_s\left(\hat{K}_s/\hat{L}_s\right)^{\alpha_s}$. Productivity may increase due to (i) a reduction in within-industry misallocation reflected by an increase in TFP_s, and/or (ii) an increase in capital per worker (K_s/L_s). For most industries, growth in TFP is relatively small, and typically of an order of magnitude lower than labor productivity growth. Therefore, the main source of growth appears to be capital deepening, i.e. that constrained firms invest more and therefore become more capital intensive (in intangible or tangible capital), while misallocation itself appears to play a smaller role. For the economy as a whole, the growth in labor productivity is 39 times higher than TFP growth (i.e., $\left(\hat{Y}-1\right)/\left(T\hat{F}P-1\right)=39$).

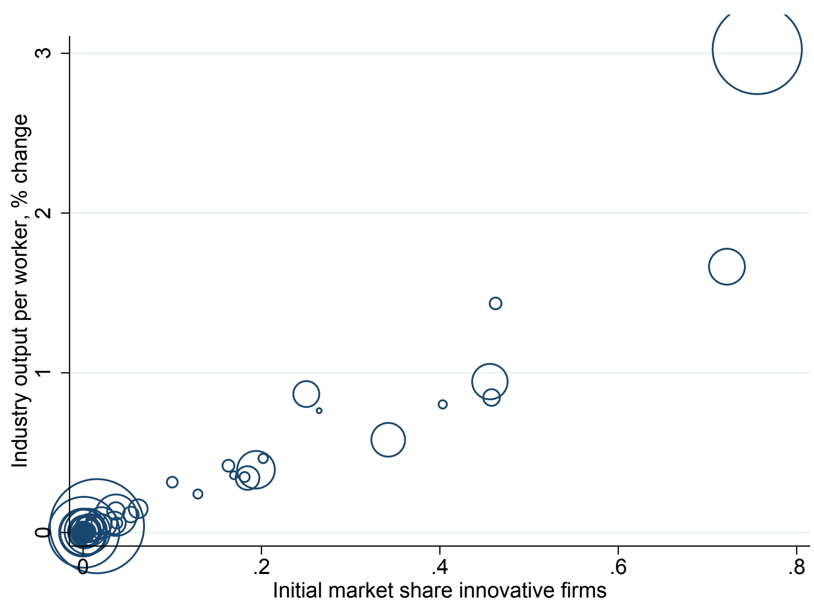
We end this section by quantifying the aggregate gains from relaxing the collateral constraint. According to the model, the increase in output per worker (and real wages) is the inverse of the reduction in the aggregate price index: $1/\hat{P}$, where the change in the aggregate

Figure 5: Firm-level employment, % change.



Note: the scatter plot shows the percentage change in employment across all firms in the economy on the vertical axis versus their initial market share on the horizontal axis.

Figure 6: Industry output per worker, % change.



Note: The plot shows the percentage change in output per worker by industry on the vertical axis and the industry market share of the innovative – treated – firms in the respective industries on the horizontal axis.

price index is:

$$\hat{P} = \prod_s \hat{P}_s^{\beta_s}.$$

By using the initial observed expenditure shares, β_s, and the $\hat{P}_s$ from equation (5), we obtain $\hat{P} = 1.006$. Multiplying this by aggregate value added in our data yields an increase in output of 6.4 billion NOK, or 0.62 billion USD using the current exchange rate.

For comparison, we also perform a back-of-the-envelope exercise that does not rely on the full model. The total implicit cost of the collateral constraint is $r\,(\tau - 1)\,K$, where K is the initial aggregate capital stock for treated firms. According to our data, the median bank interest rate is $r = 0.07$ during the period of observation, and the median credit constraint is $\tau = 1.12$ (see above). This yields a total implicit cost of the collateral constraint of 7.5 billion NOK, or 0.73 billion USD using the current change rate. We find it reassuring that the full model and the back-of-the-envelope exercise produces relatively similar magnitudes.

Is the quantified gain that arose over a three year period a small or large number? As a comparison, the total value of subsidies given by the main governmental agency for innovation and industrial policy in Norway were 5.3 billion NOK in 2021. The economic magnitude is thus substantial, and our results point to the importance of improved regulation on allocation and economic growth.

6 Concluding Remarks

We investigate the effect of improved access to collateral, and thus to credit, for innovative firms for credit, firm performance, patenting and equity funding. We find that improved pledgeability of patents has a significant positive impact on firms' access to credit: They are more likely to get bank loans, reduce their share of short term debt and increase their number of bank connections. Our findings also indicate that improved access to credit had a benign impact on firm performance, innovation and equity funding.

Our quantitative results indicate that the removal of the collateral constraint increases labor productivity. We find that industry output per worker increased by up to three percent, and were concentrated in the sectors in the economy dominated by innovative and credit constrained firms. The economic magnitude of the gains are substantial, and they are primarily driven by capital deepening, whereas within-industry misallocation plays a smaller role.

The results suggest that policies to increase the pledgeability of intangible capital are important in alleviating financial constraints on innovation, and underscores the importance of regulation as means of promoting innovation and growth.

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Appendix

A Solving the Model

A.1 Sales, employment and capital

In this section, we derive the expressions presented in the main text of the paper.

Sales. Firm-level sales are

$$\begin{aligned} S_{si} &= \left(p_{si}/P_s\right)^{1-\sigma}\beta_s S \\ &= \left(\frac{\sigma}{\sigma-1}\kappa r^{\alpha_s} w^{1-\alpha_s}\right)^{1-\sigma} A_{si}^{\sigma-1}\tau_i^{\alpha_s(1-\sigma)} P_s^{\sigma-1}\theta_s S, \end{aligned} \tag{8}$$

where S is aggregate sales.

Employment. $1-\alpha_s$ is the firm's labor share, i.e. $1-\alpha_s = wL_{si}/Costs_{si}$, and sales are a mark-up over costs, $S_{si} = \left[\sigma/\left(\sigma-1\right)\right] Costs_{si}$. Combining those expressions and solving for L_{si} yields

$$\begin{aligned} L_{si} &= \left(1-\alpha_s\right)\frac{\sigma-1}{\sigma}\frac{1}{w}S_{si} \\ &= \left(1-\alpha_s\right)\frac{\sigma-1}{\sigma}\frac{1}{w}\left(\frac{\sigma}{\sigma-1}\kappa r^{\alpha_s} w^{1-\alpha_s}\right)^{1-\sigma} A_{si}^{\sigma-1}\tau_i^{\alpha_s(1-\sigma)} P_s^{\sigma-1}\theta_s S. \end{aligned} \tag{9}$$

Industry employment can be written

$$\begin{aligned} L_s &= \sum_i L_{si} = \sum_i \left(1-\alpha_s\right)\frac{\sigma-1}{\sigma}\frac{1}{w}S_{si} \\ &= \left(1-\alpha_s\right)\frac{\sigma-1}{\sigma}\frac{1}{w}\theta_s S. \end{aligned}$$

Capital. The capital-labor ratio is

$$\frac{K_{si}}{L_{si}} = \frac{\alpha_s}{1-\alpha_s}\frac{w}{\tau_{si} r}.$$

Firm-level capital is therefore

$$K_{si} = \frac{1}{r}\alpha_s\frac{\sigma-1}{\sigma}\left(\frac{\sigma}{\sigma-1}\kappa r^{\alpha_s} w^{1-\alpha_s}\right)^{1-\sigma} A_{si}^{\sigma-1}\tau_i^{\alpha_s(1-\sigma)-1} P_s^{\sigma-1}\theta_s S. \tag{10}$$

The industry capital stock is

$$
\begin{aligned}
K_s &= \sum_i \frac{\alpha_s}{1-\alpha_s} \frac{w}{\tau_{si} r} L_{si} \\
&= \frac{\alpha_s}{1-\alpha_s} \frac{w}{r} \sum_i \frac{1}{\tau_{si}} \left(1-\alpha_s\right) \frac{\sigma-1}{\sigma} \frac{1}{w} S_{si} \\
&= \alpha_s \frac{1}{r} \frac{\sigma-1}{\sigma} \sum_i \frac{1}{\tau_{si}} S_{si} \\
&= \alpha_s \theta_s \frac{1}{r} \frac{\sigma-1}{\sigma} S \sum_i \omega_{si} \frac{1}{\tau_{si}},
\end{aligned}
$$

where ω_{si} is the industry market shares, $\omega_{si} = S_{si}/\sum_i S_{si}$.

Labor productivity. Firm-level labor productivity is

$$
\begin{aligned}
\frac{Y_{si}}{L_{si}} &= \frac{S_{si}/p_{si}}{\left(1-\alpha_s\right) S_{si} \frac{\sigma-1}{\sigma} \frac{1}{w}} \\
&= \frac{\sigma}{\sigma-1} \frac{1}{1-\alpha_s} w p_{si}^{-1} \\
&= w \frac{1}{1-\alpha_s} A_{si} \left(\kappa \left(\tau_{si} r\right)^{\alpha_s} w^{1-\alpha_s}\right)^{-1}.
\end{aligned}
$$

Industry output is $Y_s = S_s/P_s = \theta_s S/P_s$. Therefore, industry labor productivity is

$$
\begin{aligned}
\frac{Y_s}{L_s} &= \frac{\theta_s S/P_s}{\left(1-\alpha_s\right) \frac{\sigma-1}{\sigma} \frac{1}{w} \theta_s S} \\
&= \frac{1}{1-\alpha_s} \frac{\sigma}{\sigma-1} \frac{w}{P_s}.
\end{aligned}
$$

Aggregate sales. We end by solving for aggregate sales S. In equilibrium total sales equal total income. Income equals wage and capital income plus profits (which we assume is rebated back to workers). Total profits are $\Pi = S/\sigma$. Total capital income is $\sum_s \alpha_s \times Costs_s$, where $Costs_s = S_s \left(\sigma - 1\right)/\sigma$. In sum, we get

$$
\begin{aligned}
S &= wL + \frac{S}{\sigma} + \sum_s \alpha_s \frac{\sigma-1}{\sigma} S_s. \\
&= wL + \frac{S}{\sigma} + \frac{\sigma-1}{\sigma} S \sum_s \theta_s \alpha_s
\end{aligned}
$$

Rearranging,

$$
S = \frac{\sigma}{\sigma-1} \frac{1}{1-\sum_s \theta_s \alpha_s} wL.
$$

Since the wage is the numéraire, S is a constant and only a function of the parameters

σ, θ_s, α_s and L.

A.2 Comparative Statics

We proceed by deriving the change in equilibrium outcomes. Recall that we focus on an initial equilibrium with arbitrary credit constraints τ_{si}, and a counterfactual equilibrium without credit constraints, $\tau_{si} = 1$ for all i.

Using equations (8), (9) and (10), the relative changes in firm sales, employment and capital stock are

$$\begin{aligned}\hat{S}_{si} &= \left(\frac{\tau_i}{\hat{r}}\right)^{\alpha_s(\sigma-1)} \hat{P}_s^{\sigma-1} \\ \hat{L}_{si} &= \left(\frac{\tau_i}{\hat{r}}\right)^{\alpha_s(\sigma-1)} \hat{P}_s^{\sigma-1} \\ \hat{K}_{si} &= \left(\frac{\tau_i}{\hat{r}}\right)^{\alpha_s(\sigma-1)+1} \hat{P}_s^{\sigma-1}.\end{aligned}$$

Under the assumption that r is exogenous, $\hat{r} = 1$ which yields the expression in equation (4) the main text.

The change in the sector price index is

$$\begin{aligned}\hat{P}_s^{1-\sigma} &= \frac{\sum_i \left(p'_{si}\right)^{1-\sigma}}{\sum_i p_{si}^{1-\sigma}} \\ &= \hat{r}^{\alpha_s(1-\sigma)} \frac{\sum_i A_{si}^{\sigma-1}\left(\tau'_i\right)^{\alpha_s(1-\sigma)}}{\sum_i A_{si}^{\sigma-1}\tau_i^{\alpha_s(1-\sigma)}} \\ &= \hat{r}^{\alpha_s(1-\sigma)} \sum_i \omega_{si}\tau_i^{\alpha_s(\sigma-1)},\end{aligned}$$

which yields the expression in equation (5) in the main text (when $\hat{r} = 1$).

The change in the industry capital stock is

$$\begin{aligned}\hat{K}_s &= \frac{\alpha_s\theta_s\frac{1}{r}\frac{\sigma-1}{\sigma}S'}{\alpha_s\theta_s\frac{1}{r}\frac{\sigma-1}{\sigma}S\sum_i \omega_{si}\frac{1}{\tau_i}} \\ &= \left(\hat{r}\sum_i \omega_{si}\tau_i^{-1}\right)^{-1},\end{aligned}$$

and the change in sector output, and output per worker, is simply $\hat{Y}_s = 1/\hat{P}_s$.

Industry TFP. The change in industry output is $\hat{Y}_s = T\hat{F}P_s\hat{K}_s^{\alpha_s}\hat{L}_s^{1-\alpha_s}$. We have already derived expressions for $\hat{Y}_s$, $\hat{K}_s$ and $\hat{L}_s$. We insert these expressions and solve for

$$T\hat{F}P_s :$$

$$\left[\sum_{i=1}^{M_s}\omega_{si}\tau_i^{\alpha_s(\sigma-1)}\right]^{1/(\sigma-1)}\hat{r}^{-\alpha_s} = T\hat{F}P_s\left(\hat{r}\sum_i \omega_{si}\tau_i^{-1}\right)^{-\alpha_s}$$

$$T\hat{F}P_s = \left[\sum_i \omega_{si}\tau_i^{-1}\right]^{\alpha_s}\left[\sum_{i=1}^{M_s}\omega_{si}\tau_i^{\alpha_s(\sigma-1)}\right]^{1/(\sigma-1)},$$

which yields the expression in equation (7) in the main text.

A.3 Endogenous interest rate

In this section, we solve the model under the assumption that aggregate capital supply is perfectly inelastic and fixed at K and the interest rate r is endogenous.

Equilibrium in the capital market requires that demand for capital equals the fixed supply K^S, $\sum_s K_s = K^S$. Inserting the expression for K_s from above, we get

$$\sum_s \alpha_s\theta_s\frac{1}{r}\frac{\sigma-1}{\sigma}S\sum_i\omega_{si}\frac{1}{\tau_{si}} = K^S$$

$$r = \frac{\sigma-1}{\sigma}\frac{1}{K^S}S\sum_s\theta_s\alpha_s\sum_i\omega_{si}\frac{1}{\tau_{si}}.$$

The relative change in the interest rate is then

$$\hat{r} = \frac{\sum_s\theta_s\alpha_s}{\sum_s\theta_s\alpha_s\sum_i\omega_{si}\tau_{si}^{-1}}.$$

Results. Inserting values for the expression above yields $\hat{r} = 1.013$, i.e. the interest rate increases by 1.3 percent. Next, we decompose output per worker as above. For the economy as a whole, growth in labor productivity is 66 percent higher than TFP growth (i.e., $\left(\hat{Y}-1\right)/\left(T\hat{F}P-1\right) = 1.66$. This suggests that slightly more than half growth in output per worker is due to a fall in misallocation within industries, whereas the remaining part is due to a fall in misallocation across industries (i.e. that the capital stock increases in one sector s and declines in a different sector s').