Strapped for cash: The role of financial constraints for innovating firms, misallocation and aggregate productivity growth

By Esther Ann Bøler and Andreas Moxnes and Karen Helene Ulltveit-Moe*

We analyze the impact of reduced financial constraints on innovating firms' performance and access to credit using a reform that allowed firms to use patents as collateral. We develop a theoretical framework to guide the analysis and quantify the aggregate impact of reduced financial constraints on misallocation and productivity by mapping data moments, reduced form results and model counterparts. Our empirical results suggest that reduced financial constraints led to an increase in firms' capital stock and bank debt. Parameterizing the model we find quantitatively large gains in output per worker in the sectors of the economy dominated by constrained firms.

Investments in intangibles and research and development (R&D) are becoming increasingly important (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 two main 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 hinder 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.

This paper aims to close the gap between the literature on firm-level effects of financial constraints and the literature on aggregate effects of financial constraints and misallocation. Zooming in on a particular type of intangibles, patents, we make use of a reform that allowed firms to use patents as stand-alone collateral and estimate the reduced-form impact of improved access to collateral on firms' performance and access to credit. Furthermore, we develop a theoretical framework that allows us to study the economy-wide effects of reduced financial

* Bøler: Imperial Business School (e.boler@imperial.ac.uk); Moxnes: BI Norwegian Business School (andreas.moxnes@bi.no); Ulltveit-Moe: University of Oslo (k.h.ulltveit-moe@econ.uio.no). We thank Johannes Boehm, Magne Mogstad, Veronica Rappoport, Cedric Schneider, and participants at various seminars and conferences for valuable comments and discussion. We would also like to thank the referees and the editor for comments that have allowed us to improve the article. The project has received funding from the Norwegian Ministry of Trade, Industry and Fisheries (INNOPROD) and the European Research Council (ERC) under the European Union Horizon 2020 Research and Innovation programme (grant agreement No 101141494). Data from Statistics Norway has been crucial for this project.

constraints on misallocation and output. We parameterize the model using simple and well-identified moments from the reduced-form analysis in order to study allocative efficiency and aggregate productivity growth.

We first develop a parsimonious model of monopolistic competition with potentially capital constrained heterogeneous firms, in the spirit of Melitz (2003) and Hsieh and Klenow (2009). The model serves two purposes. First, we use it to develop testable reduced-form hypotheses about the impact of the collateral reform on firm performance. Second, we use the model as the basis for a quantitative framework which allows us to conduct a counterfactual analysis to quantify industry and aggregate effects of the collateral reform. The quantitative framework has two main strengths: First, it allows for any initial distribution of constraints across firms, as well as heterogeneity in the change in constraints across firms when the collateral reform was introduced. Second, the framework provides a simple mapping between data moments, reduced form results, and model counterparts.

In the first part of the article, we analyze the firm-level impact of a collateral reform. According to Norwegian law, patents could not be used as stand-alone collateral before 2015.[1] The reform allowed firms with a patent portfolio to use their patents as stand-alone collateral. Our hypothesis is that the reform reduced financial constraints for firms that hold patents. We expect this to be reflected in increased capital investments enabled by improved access to credit. 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. We investigate the effect of improved access to collateral on firms' capital stock and marginal revenue product of capital (MRPK), and the direct impact of the reform on firms' access to credit. Our firm-level analysis relies on unusually rich panel data from Norway. The data set includes details on firms' income, costs, assets, debt and patenting, and covers the universe of firms in the economy.

Our reduced-form results show that lifting the intangible collateral constraint led to an increase in patenting firms' capital stock and a decline in MRPK. Investigating firms' external funding, we find that the likelihood of bank borrowing for the treatment relative to the control group increases and that firms in the treatment group increased bank borrowing. We also find that short term debt declines, suggesting that less secure short term debt was converted to long-term debt backed by collateral, and that treated firms obtained more lines of credit (i.e., more bank connections), after the reform.

In the second part of the article, we conduct a counterfactual analysis of the impact of reduced financial constraints on misallocation and aggregate productivity growth. According to the model, the impact of reduced credit constraints for a subset of firms on misallocation is ambiguous: if credit frictions are reduced for a firm with relatively high initial frictions (relative to other firms), then misallo-

[1] Internationally, patents are frequently used as collateral (see, e.g. Mann, 2018).

cation decreases. On the other hand, if credit frictions are reduced for a firm with relatively low initial frictions, then misallocation may increase because dispersion in frictions in the economy is exacerbated. Empirically, we can determine the sign of the effect by using three data points: each firm's initial share of sales (relative to total sales in the industry), each firm's initial share of capital (relative to total capital in the industry), and each firm's reduction in the financial constraint.

In addition to misallocation, a reduction in financial constraints also affects output per worker through capital deepening. If the aggregate supply of capital is elastic, then firms affected by the reform will invest more and become more capital intensive, without completely crowding out capital from unaffected firms.

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. While our results are specific to a given context, we believe this methodology can be useful for analyzing a wide range of economic questions in a parsimonious and transparent framework, and is complementary to the non-parametric approach by Sraer and Thesmar (2023).

Our quantitative results indicate that improved access to collateral increased aggregate productivity. Industry output per worker grew by up to three percent, and the gains were concentrated in sectors of the economy dominated by firms with a patent portfolio. The effect on misallocation, and thus total factor productivity, is relatively small, and typically of an order of magnitude lower than the effect on labor productivity growth. Therefore, the positive impact of the reform on productivity is primarily driven by capital deepening, i.e. firms affected by the reform become more capital intensive. The quantified aggregate gains are substantial, and similar in magnitude to the total value of innovation subsidies granted to firms in 2015. Our analysis underscores the attractiveness of productivity-enhancing regulation as an alternative to government subsidies.

The paper makes contributions to three distinct areas of research. First, we contribute to the literature on financial constrains and misallocation (see e.g. Bau and Matray (2023), Buera, Kaboski and Shin (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) and De Ridder (2022)).[2] To our knowledge, this is the first paper to focus on the impact of collateral constraints related to intangible assets on misallocation.[3] 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. Like Sraer and Thesmar (2023) we offer a method to measure allocative efficiency in a quasi-experimental setting. Our method is complementary to theirs as it is parametric rather than non-parametric and does not rest on specific assumptions regarding

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

[3]In contemporaneous work focusing on exporting, Finlay (2024) parameterizes a model of misallocation using a directed credit policy towards selected industrial sectors in India as a source of exogenous variation.

the distribution of MRPK or the magnitude of the shock, nor do we need to make any assumptions regarding the heterogeneity in the frictions that are affected by the shock.

Second, 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 innovating firms.

Third, the paper contributes to the literature on the role of intangible assets in corporate finance. Of particular relevance are the papers by Mann (2018), analyzing the impact on debt and innovation when creditor rights to patents are strengthened, and Farre-Mensa, Hegde and Ljungqvist (2020), showing that getting a patent granted increases sales and the chances of securing a loan by pledging the patent as collateral.[4] Compared to this line of research, our paper not only estimates the effect of improved pledgeability, but also quantifies the aggregate implications on misallocation and productivity growth.[5] 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.

The remainder of this paper is organized as follows. Section I presents a theoretical framework which we use to guide the empirical analysis as well as our quantification of aggregate effects. Section II describes the collateral reform and the data, and presents the empirical model and empirical results. Section III quantifies the impact of reduced financial constraints on resource allocation and productivity growth. Section IV provides some concluding remarks.

I. Theoretical Framework

In this section, we present a simple model of monopolistic competition and heterogeneous firms, in the spirit of Melitz (2003) and Hsieh and Klenow (2009), to guide our analysis of financial constraints, firm performance and aggregate effects. The model serves two purposes. First, the model helps us specify reduced-form regressions to estimate the causal effects of a collateral reform on firm level outcomes (Section II). Second, we use the model to quantify how the reform

[4]Other relevant papers include Falato et al. (2022), on the importance of intangible assets in explaining the upward trend in US corporate cash holdings; Brown, Fazzari and Petersen (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, Chatelain and Ralf (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; Hochberg, Serrano and Ziedonis (2018) analyze the impact on firms' debt of thicker trading in the secondary market for patents, and Chava, Nanda and Xiao (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. See also Hall (2019) for a recent literature review.

[5]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.

affected industry and aggregate outcomes and thus allocative efficiency (Section III).

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:

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

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:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_i^{(\sigma-1)/\sigma} \right)^{\sigma/(\sigma-1)}, \tag{2}$$

where σ is the elasticity of substitution across firms and Y_i is output of firm i. We let P_s denote the corresponding sector-level CES price index, and the aggregate price index is thus $P = \prod_s P_s^{\theta_s}$. The production technology of firm i is Cobb-Douglas:

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}, \tag{3}$$

where A_i denotes productivity, L_i is labor, K_i is a CES composite of tangible and intangible capital and α is the capital cost share. The CES price index of capital is

$$r_i = \left((\tau_{Ii}\tilde{p}_I)^{1-\psi} + (\tau_{Ti}\tilde{p}_T)^{1-\psi} \right)^{1/(1-\psi)} \tag{4}$$

where ψ is the elasticity of substitution, $\tau_{ki} \geq 1$ is the wedge on intangible ($k = I$) or tangible capital ($k = T$), and $\tilde{p}_k$ is the interest rate on the two forms of capital. The wedges reflect the presence of financial constraints.

The firm is maximizing profits and is a price-taker in capital and labor markets. We follow Banerjee and Duflo (2014) and define a firm as constrained if it has less capital than the amount it would want at the current interest rate. Firms choose their capital stock such that their marginal revenue product of capital ($MRPK_i$) equals the price of capital: $MRPK_i = r_i$. For constrained firms with $\tau_{ki} > 1$ for intangible and/or tangible capital, their $MRPK_i$ is higher and their capital stock is lower than in the optimal situation with no financial constraints.

Firm i's profits are then given by

$$\pi_i = p_i Y_i - wL_i - r_i K_i, \tag{5}$$

where w is the wage. Given these assumptions, the firm's optimal price is a constant mark-up over marginal costs:

$$p_i = \kappa \frac{\sigma}{\sigma - 1} \frac{r_i^{\alpha} w^{1-\alpha}}{A_i}. \tag{6}$$

where $\kappa \equiv \alpha^{-\alpha} (1-\alpha)^{-(1-\alpha)}$. In Appendix B, we show that a firm's employment and capital stock can be written as

$$L_i = D_s \frac{1-\alpha}{w} A_i^{\sigma-1} r_i^{\alpha(1-\sigma)} \tag{7}$$

$$K_i = D_s \alpha A_i^{\sigma-1} r_i^{\alpha(1-\sigma)-1}, \tag{8}$$

where $D_s \equiv \frac{\sigma-1}{\sigma} \left(\frac{\sigma}{\sigma-1} \kappa w^{1-\alpha} \right)^{1-\sigma} P_s^{\sigma-1} \theta_s S$ is an industry-specific demand shifter with S denoting total sales. The marginal revenue product of capital is

$$MRPK_i = \alpha S_i / K_i \tag{9}$$

where S_i denotes firm sales.

Section III provides further details on the general equilibrium, counterfactual analyses and quantification of the model.

II. Empirical Analysis

Next, we use a reform to the law on collateral in Norway as a natural experiment to investigate the effects of reduced credit constraints. We start by describing the reform and the rich data at hand. Second, we develop an empirical model and identification strategy based on the theoretical model presented above, allowing us to provide firm-level evidence on the effects of reduced credit constraints on firms' capital stock and marginal revenue product of capital. We moreover address the direct effects of improved access to collateral on firms' access to credit.

A. Background

The reform to the law on collateral in Norway improved the pledgeability of patents by allowing firms to use patents and patent applications as stand-alone collateral.[6] The reform came into force on July 1st 2015, less than 6 months after the details were announced.[7]

[6]The use of collateral is regulated by law. For details on the law, see https://lovdata.no/lov/1980-02-08-2/4-12.

[7]Prior to this, a patent could only be used as collateral (i) in conjunction with machinery and equipment and/or (ii) if the patent is utilized in current production.

The reform was introduced 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 allow for the use of patents as collateral.[8] 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).

The reform offers several advantages for assessing the effects of reduced credit constraints on firm performance. First, it was a relatively clean policy experiment, as the reform was not part of a greater overhaul of industrial policy. Second, the reform itself was not initiated in response to major economic shocks to the economy. Third, although the topic had been discussed for quite some years, the details of the reform were announced only months prior to the introduction of the reform, which limited the scope for anticipation effects and strategic behavior. Anticipation effects and strategic behavior are also limited by the fact that patents typically are the result of many years of research and/or development, which inhibits short term adjustment.

B. *Data*

The empirical analysis is based on four data sets. The first is administrative firm register data from Statistics Norway. The data set covers the universe of firms across all sectors and provides information on the date of the entry and exit of each individual firm, allowing us to compute 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. Since 85 percent of Norwegian firms with one or more employees are joint-stock firms, this means that we cover close to the universe of firms in Norway. The income statement and balance sheet data are based on data from annual accounting 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.

The third data set is detailed 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. This allows us to compute the interest rate that firms are facing related to their loans.[9]

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

[9] Unfortunately, we do not have information about whether or what type of collateral is associated with a given loan.

The fourth data set is based on the universe of published patent applications submitted to the Norwegian Industrial Property Office. For each patent application we have detailed information including the year of filing and identity of the applicant, 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.

C. *Empirical Model*

In order to identify the impact of improved access to financing we specify a difference-in-difference model based on the theoretical model presented above. According to equation (8), the firm's log capital stock can be written as

$$\ln K_i = \ln (D_s \alpha) + (\sigma - 1) \ln A_i + [\alpha (1 - \sigma) - 1] \ln r_i. \tag{10}$$

Taking this relationship to the data, we add time subscripts to K_i, D_s and r_i and add an idiosyncratic error term ϵ_{it}. The price of capital, r_i, depends on firm specific financial frictions, see equation (4), and consists of a time-invariant component and a time-varying component:

$$\ln r_{it} = \psi_i + \eta Pat_i \times Post_t, \tag{11}$$

where Pat_i takes the value one if the firm is exposed to the policy change and $Post_t$ takes the value one after the policy change is implemented in 2015. In practice, we let $Pat_i = 1$ for firms with at least one patent application in the five years prior to the reform, i.e. between 2010 and 2015, i.e. that firm i has an ex-ante patent portfolio that was not pledgeable before the reform. Collecting terms and introducing firm fixed effects (υ_i) and time varying industry fixed effects (δ_{st}), yields the following baseline specification:

$$\ln K_{it} = \upsilon_i + \beta Pat_i \times Post_t + \gamma X_{i0} \times \delta_t + \delta_{st} + \varepsilon_{it}, \tag{12}$$

with $\delta_{st} = \ln \left(\frac{\alpha}{r_t} D_{st} \right)$, $\beta = \eta [\alpha (1 - \sigma) - 1]$, $\upsilon_i = [\alpha (1 - \sigma) - 1] \psi_i + (\sigma - 1) \ln A_i$, and where we also included firm-specific trends. 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 baseline specification in equation (12) compares firms with an ex-ante patent portfolio to similar firms without a patent portfolio. 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, stock of tangible assets and share of intangible assets in total fixed assets.

Equation (12) use capital as the outcome variable, and we start by considering a set of outcome variables for which we have testable predictions from the theoretical framework (see Section I). We proceed by investigating outcome variables related to the funding of firms' capital that reflect firms' access to external funding and financing costs.

Our key outcome variables include employment, sales, capital, intangible capital, and (inverse) MRPK. Capital is calculated as total fixed assets, intangible capital is calculated as the sum of intangible assets excluding deferred taxes, while inverse MRPK is calculated as the capital to sales ratio, see Section I.[10] For credit related variables, we use bank debt, both as a binary variable indicating whether the firm has a bank loan or not, and as the total value of bank debt. We also construct a variable that measures short term debt relative to total debt as reported in the balance sheet data. We compute financing costs as the firm-specific interest rate, where we take the total amount of interest payments in a given year, divided by the average value of debt in years t and $t-1$.

The control variables are log employment, log value of fixed tangible assets, the share of intangibles in total fixed assets (intangible intensity), and a dummy for whether the firm has received public funding through a government agency.

D. Descriptives

In Table 1 we present mean values for a set of key firm characteristics for treated firms versus control firms. As is evident, only a small fraction of firms in the sample hold patents: in 2014, there are around 500 firms with patents and 90,000 without. Firms with patents are different: they are larger than firms without patents in terms of both employment and assets, they have a higher share of intangible assets, they are more capital intensive, less labor intensive, less profitable (profits/output), receive more public funding and are slightly older. This highlights the need to include control variables to make our treatment and control groups more comparable.

[10]We use the inverse to avoid losing observations with zero fixed assets.

Table 1—Descriptive statistics

	Firms with $Pat_i = 0$	Firms with $Pat_i = 1$
Log employment	1.41	2.85
Log fixed tangible assets	12.71	14.95
Intangible intensity	0.04	0.21
Public funding (dummy)	0.06	0.74
Age	10.06	12.06
Capital/Sales	0.42	1.07
Labor/Sales	0.15	0.10
Profits/Sales	0.01	−0.09
N	90,314	501

Note: The data is from 2014. Intangible intensity refers to the the share of intangibles in total fixed assets. $\frac{Capital}{Sales}$ and $\frac{Profits}{Sales}$ is truncated at the 1st and 99th percentile. Capital is measured by total fixed assets. $\frac{Labor}{Sales}$ is multiplied by 100,000 and truncated at the 1st and 99th percentile.

E. Empirical Results on Firm Performance

We estimate the empirical model, see equation (12), for capital as well as for log employment, log sales, intangible capital and marginal revenue product of capital (MRPK), and report the results in Table II.E. To deal with observations with zero values in the dependent variable, we use a Pseudo Poisson maximum likelihood (PPML) estimator when the outcome variable is capital or intangible capital. We also recognize that firms face different accounting rules depending on firm size and may value assets differently. In the regressions with capital and intangible capital as outcomes, we therefore add an extra control variable that indicates which accounting rule is used (interacted with year dummies,$X_{i0} \times \delta_t$).

We find that capital stock (column (3)) and employment (column (1)) increased for the treatment relative to the control group. We find an even stronger positive and significant effect on the part of the capital stock that is intangible (see column (5)). The results suggest that the collateral reform promoted both investment and hiring among the treated firms. We also find a significant negative effect on MRPK for treated firms (column (4)). We find no increase in sales (column (2)). One potential explanation is that sales are the product of output and price. Hence, even if output is increasing, a contemporaneous decline in price will only lead to a small (or even zero) increase in revenue. We also note if we estimate the model without firm controls, we find a positive and significant effect on sales, see Section II.H. Finally, it may be that the insignificant result for sales reflects the fact that there is a lag between investment and sales, and that the post-reform sample period is rather short (2015-2018).

Our results are in general in line with the testable predictions derived above. They support the hypothesis that the policy reform led to reduced financial constraints for patenting firms.

TABLE 2—FIRM PERFORMANCE

	Log empl.	Log sales	Capital	1/MRPK	Intang. cap.
	(1)	(2)	(3)	(4)	(5)
$Post_t \times Pat_i$	0.089***	0.022	0.223**	0.246***	1.133***
	(0.030)	(0.041)	(0.103)	(0.080)	(0.286)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	PPML	OLS	PPML
Observations	763,161	748,284	753,992	739,488	118,605

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. 1/MRPK is measured by total fixed assets divided by operating income. 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 and intangible capital as outcome we add an extra control variable to account for different accounting rules. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

HETEROGENEITY. — We also explore heterogeneous responses to improved access to collateral. In particular we focus on young firms. We do so by estimating split regression for old and young firms, where a firm is defined as young if it is six years or younger in 2015. The results are reported in Tables 3 and 4. We find stronger effects for young firms on employment, sales, capital and MRPK. On the other hand, the results on intangible capital are stronger for older firms.

Table 3—Firm Performance – Old firms

	Log empl. (1)	Log sales (2)	Capital (3)	1/MRPK (4)	Intang. cap. (5)
$Post_t \times Pat_i$	0.065^{**}	0.011	0.223^{**}	0.162^{**}	1.128^{***}
	(0.032)	(0.042)	(0.106)	(0.077)	(0.298)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	PPML	OLS	PPML
Observations	573,526	561,200	565,171	553,787	90,587

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. 1/MRPK is measured by total fixed assets divided by operating income. 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 and intangible capital as outcome we add an extra control variable to account for different accounting rules. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4—Firm Performance – Young firms

	Log empl. (1)	Log sales (2)	Capital (3)	1/MRPK (4)	Intang. cap. (5)
$Post_t \times Pat_i$	0.272^{***}	0.233^{*}	0.520^{***}	0.730^{***}	-0.170
	(0.032)	(0.135)	(0.094)	(0.333)	(0.151)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	PPML	OLS	PPML
Observations	189,618	187,064	189,453	185,681	27,961

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. 1/MRPK is measured by total fixed assets divided by operating income. 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 and intangible capital as outcome we add an extra control variable to account for different accounting rules. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F. Empirical Results on Credit

We proceed by estimating the same empirical model as above, but now for a set of outcomes related to credit. The results are reported in Table 5. 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 firms getting bank loans. Column (2) reports the results on bank debt in levels, and also here we find a positive and significant response. Column (3) shows that the share of short term debt declines by 2.3 percentage points, suggesting that less secure short term debt was converted to long-term debt backed by collateral. The result in column (4) shows that the number of bank connections increased, suggesting that treated firms obtained more lines of credit after the reform. Finally, column (5) reports results for the firm-specific interest rate. We find no significant change in the firm specific 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. Note, however, that the result on interest rates is conditional on firms having a bank loan, i.e. we cannot conclude whether the price of credit changed for firms that chose not to get a bank loan. In summary, our results suggest that the reform allowed firms to extend their borrowing and increased firms' probability of getting bank loan without facing an increase in interest rate.

Table 5—Credit Access

	Bank dummy dummy	Bank debt	$\frac{Short\ Debt}{Total\ Debt}$	No Banks	Interest rate
	(1)	(2)	(3)	(4)	(5)
$Post_t \times Pat_i$	0.049***	0.594$***$	-0.023**	0.146***	0.001
	(0.019)	(0.175)	(0.010)	(0.041)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	OLS	OLS	OLS
Observations	763,161	501,278	758,311	763,161	336,497

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, and a dummy for public funding, all interacted with year dummies. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Heterogeneity. — Again we explore heterogeneous responses and address the question of the policy mattered relatively more for young firms than for older firms and estimate split regressions for the two groups of firms. The results are reported in Tables 6 and 7. We find a stronger effect for bank debt for young firms on the extensive margin. We also find a stronger effect on short term debt and number of bank connections for young firms.

TABLE 6—CREDIT ACCESS – OLD FIRMS

	Bank dummy	Bank debt	$\frac{Short\ Debt}{Total\ Debt}$	No of Banks	Interest rate
	(1)	(2)	(3)	(4)	(5)
$Post_t \times Pat_i$	0.038*	0.593***	−0.010	0.132***	0.001
	(0.020)	(0.180)	(0.010)	(0.044)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	OLS	OLS	OLS
Observations	573,526	390,902	570,037	573,526	264,224

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, and a dummy for public funding, all interacted with year dummies. $^{*}\,p < 0.1$, $^{**}\,p < 0.05$, $^{***}\,p < 0.01$.

Table 7—Credit Access – Young firms

	Bank dummy	Bank debt	$\frac{Short\ Debt}{Total\ Debt}$	No of Banks	Interest rate
	(1)	(2)	(3)	(4)	(5)
$Post_t \times Pat_i$	0.113^{**}	0.985	-0.112^{***}	0.227^{**}	0.007
	(0.051)	(0.659)	(0.030)	(0.102)	(0.007)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	OLS	OLS	OLS
Observations	189,618	110,341	188,257	189,618	72,261

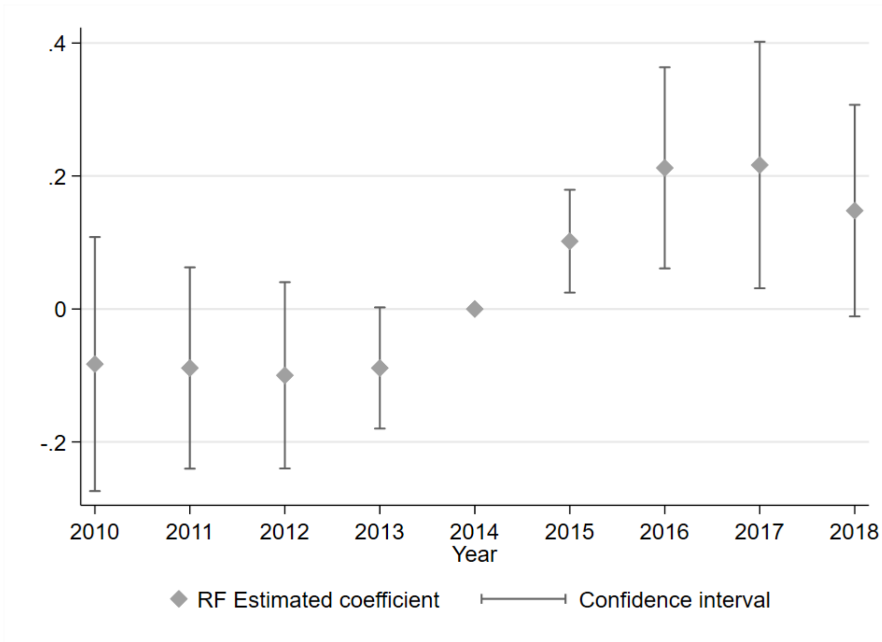
Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, and a dummy for public funding, all interacted with year dummies. $^{*}\,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

G. Pre-trends

A potential concern is that treated firms face different pre-trends compared to those in the control group prior to the policy reform. Identification of the treatment effect requires similar pre-trends for the two groups of firms. We investigate this using a plot of pre-trends as well as a falsification test.

First, we plot pre-trends for a key outcome variable, capital. Figure II.G plots the coefficients from a dynamic event study specification, where the $Post_t$ dummy is replaced by dummies for individual years. The pre-trends are overall similar for the two groups.

FIGURE 1. PRE-TRENDS: CAPITAL



Note: The figure plots the coefficients from a dynamic event study specification estimated using PPML. The bars indicate 90% confidence intervals.

Second, we run three placebo exercises, estimating equation (12) for different time periods when no reform was implemented. These exercises allow us to isolate the effect of having patented from that of the reform itself. In the first, we consider a sample based on the period 2005 to 2012 and use 2010 to 2012 as the treatment period. We let the variable $Pat09_i$ take the value one if firm i had at least one patent application between 2005 and 2009, and zero otherwise. In the second estimation, we use 2006 to 2013 as sample period and 2011 to 2013 as the treatment period. The variable $Pat10_i$ takes the value one if firm i had at least one patent application between 2006 and 2010, and zero otherwise. In the third estimation, we use the 2007 to 2014 as sample period and 2012 to 2014 as the treatment period. The variable $Pat11_i$ takes the value one if firm i had at least one patent application between 2007 and 2011, and zero otherwise. This way, we can keep the sample lengths the same as in our main exercise, and we avoid including any years in which there was actually a reform. The results of all three regressions are reported in Table 8.[11] The point estimates are close to zero and insignificant for most of the outcomes, suggesting that the treatment and control groups are not on differential trends. The one exception is intangible capital,

[11]We only report results for our main variables to limit the amount of tables. Results for the remaining outcome variables also support our hypothesis, and are available upon request.

where the coefficient is significant, but with a negative sign for all periods.

TABLE 8—PLACEBO

	Bank loan dummy (1)	Bank debt (2)	Capital (3)	1/MRPK (4)	Intang. capital (5)
Panel a)					
$Post2009 \times Pat09_i$	0.008	-0.065	0.023	-0.075	-0.982^{***}
	(0.011)	(0.208)	(0.067)	(0.060)	(0.358)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	595,510	408,585	590,741	578,028	93,320
Panel b)					
$Post2010 \times Pat10_i$	0.018	-0.139	-0.111	0.033	-0.636^{**}
	(0.011)	(0.163)	(0.074)	(0.050)	(0.263)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	605,718	405,876	589,617	586,949	93,468
Panel c)					
$Post2011 \times Pat11_i$	0.017	0.229	-0.118	0.013	-0.743**
	(0.011)	(0.244)	(0.0870)	(0.055)	(0.294)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	610,133	400,147	601,471	591,243	93,805

Note: Standard errors in parenthesis are clustered on firm. The sample period is: Panel a) 2005 to 2012, Panel b) 2006 to 2013, Panel c) 2007 to 2014. Controls include pre-sample firm characteristics: log employment, log fixed tangible assets, share of intangibles in total fixed assets, and a dummy for public funding, all interacted with year dummies. With capital and intangible capital as outcome we add an extra control variable to account for different accounting rules. 1/MRPK is measured by total fixed assets divided by operating income. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

H. Robustness

Unconstrained firms: One may object that some firms in our treatment group were not credit constrained prior to the reform, as some firms may have abundant sources of other collateral than patents. These firms should presumably not be affected by the reform. As a robustness check, we use a common measure of credit constraints and re-estimate the model on a subset of firms that are unlikely to be constrained. Specifically, we use the accounting data to compute an indicator of firms' cashflow relative to total assets, measured by the ratio of EBITDA to total assets.[12] We limit the sample to firms with an above median EBITDA-to-assets ratio for their industry in 2014 and reestimate the model, focusing on the key outcome variables related to financing and firm performance.. The results are presented in Table 9, and show that - in line with our hypothesis - unconstrained firms did in general not respond to the reform. For bank debt we actually find a negative response, albeit with slightly high standard errors.[13]

TABLE 9—FIRM PERFORMANCE: UNCONSTRAINED FIRMS

	Bank loan dummy	Bank debt	Capital	1/MRPK	Intang. capital
	(1)	(2)	(3)	(4)	(5)
$Post_t \times Pat_i$	0.030	-0.510*	0.057	-0.006	0.471
	(0.037)	(0.280)	(0.168)	(0.070)	(0.751)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	367,248	222,996	343,327	361,465	41,395

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. 1/MRPK is measured by total fixed assets divided by operating income. 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 and intangible capital as outcome we add an extra control variable to account for different accounting rules. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

No controls: Recent literature has highlighted how controlling for ex-ante differences in firm characteristics can bias the estimates from a difference in differences if due to mean reversion (Maksimovic, Phillips and Yang, 2023). To alleviate concerns related to this, we rerun our main specification for firm performance and credit outcomes without the controls for firm characteristics. The results are presented in Table 10 and Table 11. With the exception of capital, which is

[12] As our results indicate that credit constrained firms struggle to access external debt financing, we want to avoid using a measure of credit constraints that relies on debt.

[13] We only report results for our main variables to limit the amount of tables. The results for the remaining outcome variables also support our hypothesis, and are available upon request.

positive but no longer significant, all of the results are robust to the exclusion of firm controls. We note that when we exclude firm controls we also find a positive impact on sales.

Table 10—Firm Performance: No Firm Controls

	Log empl. (1)	Log sales (2)	Capital (3)	1/MRPK (4)	Intang. capital (5)
$Post_t \times Pat_i$	0.094***	0.084***	0.106	0.189***	1.345***
	(0.031)	(0.041)	(0.121)	(0.079)	(0.528)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	No	No	No	No	No
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	PPML	OLS	PPML
Observations	798,305	780,558	756,784	771,488	120,309

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. Capital is measured by total fixed assets. 1/MRPK is measured by total fixed assets divided by operating income. With capital and intangible capital as outcome we add an extra control variable to account for different accounting rules. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11—Credit Access: No Firm Controls

	Bank loan dummy (1)	Bank debt (2)	$\frac{Short\ Debt}{Total\ Debt}$ (3)	No of Banks (4)	Interest rate (5)
$Post_t \times Pat_i$	0.077***	0.633***	-0.019***	0.235***	0.001
	(0.019)	(0.186)	(0.010)	(0.040)	(0.003)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	No	No	No	No	No
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	OLS	OLS	OLS
Observations	798,305	507,922	792,303	798,305	339,559

Note: Standard errors in parenthesis are clustered on firm. The sample period is 2010 to 2018. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Patent portfolio: We also check whether the estimated effects vary depending on how many patents firms have filed before the reform was introduced. We split firms into bins based on their pre-reform patent history, and create a new treatment dummy variable that takes the value of 0 for firms with no patents, 1 for firms with one patent, and 2 for firms with more than one patent. The results can be found in Table D1 in Appendix D. For most of our outcome variables, we find that the effects are stronger the more patents firms have. Intuitively, this makes sense, because the more patents a firm has, the larger the scope for using these patents as collateral after the reform was introduced.[14]

Intangible intensity: We also want to make sure that we are not biasing our estimates by including the value of patents in our measure of intangible intensity that we use as a control variable. Recall that to construct our original measure of intangible intensity (share of intangibles in total fixed assets), we take the value of R&D, patents and goodwill from the balance sheet. We now construct an amended measure of intangible intensity where we remove the value of patents, and run our baseline estimations with this new measure. The results can be found in Table D2 in the Appendix D, and show that our baseline results are not affected.

III. The Aggregate Impact on Misallocation and Productivity Growth

We now turn to study the implications of our findings for industry and aggregate outcomes. We build on the theoretical framework presented in Section I and use exact hat algebra (Dekle, Eaton and Kortum, 2008) as means of conducting comparative statics. We proceed by quantifying the model using the empirical results from Section II and present results from the quantitative analysis focusing on two important sources of productivity growth: reduced misallocation and increased capital deepening.

A. *Comparative Statics*

The model can be solved in changes following the "exact hat algebra" approach by Dekle, Eaton and Kortum (2008). We focus on an initial equilibrium with arbitrary pre-reform credit constraints r_i, and a counterfactual (post-reform) equilibrium with credit constraints, r'_i, holding all else constant. In the counterfactual, we consider a change in r_i for the treatment firms, while we let r_i remain constant for the control firms. 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; either that capital supply is infinitely elastic, i.e. a small open economy assumption, or that capital supply is perfectly inelastic and fixed, i.e. a closed economy assumption. We solve the model under the former assumption, which is arguably more appropriate for a small open economy such as Norway. Nominal wages are the numraire.

[14]Ideally, we would like to be able to measure the value of a firms' patenting activity, as this would be informative of the likelihood of being able to utilize the patent as collateral. One possibility would be to use forward citations as a measure of quality. Unfortunately, our data set does not include citation data. However, as highlighted by Kogan et al. (2017), the private value of a patent need not coincide with the scientific value, and citations would better capture the latter. Since the majority of our firms are unlisted, we cannot use the method they introduce as it is based on stock market responses.

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

$$\hat{L}_i = \hat{r}_i^{\alpha(1-\sigma)} \hat{P}_s^{\sigma-1}, \tag{13}$$
$$\hat{K}_i = \hat{r}_i^{\alpha(1-\sigma)-1} \hat{P}_s^{\sigma-1}, \tag{14}$$

whereas the change in the capital price index is

$$\hat{r}_i = \left(\xi_i \left(\hat{\tau}_{Ii} \hat{\tilde{p}}_I \right)^{1-\psi} + (1-\xi_i) \left(\hat{\tau}_{Ti} \hat{\tilde{p}}_T \right)^{1-\psi} \right)^{1/(1-\psi)} \tag{15}$$

where ξ_i is the share of capital spending on intangibles, $\xi_i = \frac{I_i \tilde{p}_I}{r_i K_i}$, where I_i is the quantity of intangibles for firm i. The change in labor productivity (output relative to employment) is $\hat{Y}_i/\hat{L}_i = \hat{r}_i^{-\alpha}$.[15] For a given reduction in credit constraints for firm i, capital, employment and labor productivity increase relative to other firms in sector s. Detailed derivations are provided in Appendix Section C.

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

$$\hat{P}_s = \left[\sum_{i=1}^{M_s} \omega_i \hat{r}_i^{\alpha(1-\sigma)} \right]^{1/(1-\sigma)}, \tag{16}$$

where ω_i refers to the initial sales share of firm i in industry s, $\omega_i = S_i / \sum_{i=1}^{M_s} S_i$. The price index, therefore, declines when one or more firms in the industry experiences reduced credit constraints. From equations (14) and (16), we note that firms with no change in credit constraints, $\hat{r}_i = 1$, will contract when frictions for other firms decline, because they face more competition from firms with reduced credit constraints.

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

$$Y_s = TFP_s K_s^{\alpha} L_s^{1-\alpha}. \tag{17}$$

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

$$\hat{K}_s = \sum_{i=1}^{M_s} \zeta_i \hat{r}_i^{-1}, \tag{18}$$

[15] The relative change in *sales* per worker is $\hat{S}_i/\hat{L}_i = 1$, see Appendix Section C.

and

$$TF\hat{P}_s = \frac{\left[\sum_{i=1}^{M_s} \omega_i \hat{r}_i^{\alpha(1-\sigma)}\right]^{1/(\sigma-1)}}{\left[\sum_{i=1}^{M_s} \zeta_i \hat{r}_i^{-1}\right]^{\alpha}}, \tag{19}$$

where ζ_i refers to the initial capital share of firm i in industry s, $\zeta_i = K_i / \sum_{i=1}^{M_s} K_i$, and capital shares sum to one across firms within an industry. Furthermore, the change in industry labor productivity can be written as

$$\hat{Y}_s/\hat{L}_s = TF\hat{P}_s \left(\hat{K}_s/\hat{L}_s\right)^{\alpha}. \tag{20}$$

Using the fact that industry level employment is constant, see Appendix Section B, it follows that $\hat{L}_s = 1$, and we can rewrite (20) as

$$\hat{Y}_s/\hat{L}_s = \hat{Y}_s = 1/\hat{P}_s. \tag{21}$$

This also means that there is a simple relationship between the aggregate gains in terms of output and the price indices P_s:

$$\hat{Y} = \prod_s \hat{Y}_s^{\theta_s} = \prod_s \hat{P}_s^{-\theta_s}. \tag{22}$$

Misallocation. When $TF\hat{P}_s > 1$, within-industry misallocation is reduced, whereas when $TF\hat{P}_s < 1$ misallocation is increasing. Interestingly, the impact of a reduction in financial frictions, τ_{Ti} or τ_{Ii}, on misallocation is ex-ante ambiguous. The economic intuition is as follows: If credit frictions are reduced for a firm with high initial frictions relative to other firms, then misallocation decreases. On the other hand, if credit frictions are reduced for a firm with relatively low initial frictions, then misallocation may increase.

Aggregate productivity growth. From equation (20) 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 due to of reduced misallocation within an industry, i.e. TFP_s rises. Below, we quantify both sources of productivity growth.

B. *Quantification*

This section describes our methodology for quantifying the model and presents the results from the quantitative analysis. We aim to highlight the industry and aggregate impact of a decline in credit constraints caused by the collateral reform.

Recall that a change in credit frictions will affect firms' price of capital and in turn their capital stock, see equation (15). Recall further from Section II.C that $\beta = \eta\left[\alpha\left(1-\sigma\right)-1\right]$ identifies the log change in capital for treated relative to control firms post the reform. From equation (11), we know that $\Delta \ln r_i = \eta$ for treated firms. Thus, we can substitute for η and rewrite to get

$$\Delta \ln r_i = \beta / \left[\alpha\left(1-\sigma\right)-1\right]. \tag{23}$$

Combining the empirical estimate of β with information about the two parameters, the elasticity of substitution, σ, and the capital cost share, α, we can compute the value of $\Delta \ln r_i$. Using the sales and capital shares, ω_i and ζ_i, which are directly observed from the accounting data, we can then quantify the impact of reduced credit frictions on industry TFP (using equation (19) and the sector-level price index (using equation (16)) and in turn on employment and capital.

The sales and capital shares, ω_i and ζ_i, are directly observed from the accounting data, and refer to the year 2014, the year before the reform. A sector s is defined as a NACE 2-digit industry. The remaining variables σ and α are parameterized as follows. Based on the empirical estimates on demand elasticities by Broda and Weinstein (2006) we set the elasticity of substitution, σ, to 4, which they report as the mean value.[16] The capital cost share, α, is calculated as one minus wage costs relative to total costs, where total costs include wage costs, depreciation, interest costs plus costs of equity. We calculate α as the mean across all firms in our sample using our accounting data. [17] We summarize data and parameters in Table 12.

Table 12—Parameters

β	DiD estimate, $\ln Capital_i$	0.22	Baseline results
α	Capital cost share	0.30 (mean)	1 - (wage costs)/(total costs). Our data, 2014.
σ	Elasticity of substitution	4	Broda& Weinstein (2006)
ω_i	Sales share	Firm level	Our data, 2014.
ζ_i	Capital share	Firm level	Our data, 2014.

Our quantitative approach has an important advantage due to the fact that a change in firms' price of capital is identified from the differences-in-differences research design. Given the small economy assumption, the change in firms' price of capital translates into a direct and unbiased estimate of the change in frictions. 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.

[16]Three-digit goods (SITC-3), over the period 1990-2001.
[17]The costs of equity is computed as $\rho \times E_i$ where E_i is equity and ρ is set to 0.07, which is the median bank interest rate during the period of observation in our data.

Change in frictions: We start by assessing the magnitude of the change in frictions. Using equation (23) along with the parameters from Table 12, we calculate mean price of capital as $\hat{r} = 0.89$ for treated firms, implying that the implicit capital cost declined by 11 percent for a treated relative to a control firm. Our theoretical framework includes firm-specific wedges for both intangible and tangible capital, τ_{Ii} and τ_{Ti}. In the following, we set $\hat{\tau}_{Ii} = \hat{\tau}_{Ti} = \hat{\tau}_i$, i.e. we assume that the change in the effective price of capital is identical for both types of capital. Our choice is based on the observation that the collateral reform raised funding opportunities for both types of capital, i.e. firms treated by the reform could use new collateral to invest both in more tangible and intangible capital. We then obtain the mean change in frictions $\hat{\tau} = \hat{r} = 0.89$.

Firm-level results: Armed with this information about the magnitude of the change in frictions for the treatment firms, we analyze the impact on firm and industry outcomes according to the counterfactual. First, we document the change in employment before to after the reform. According to the model, we expect treated firms to expand as credit frictions decline, whereas control group firms are contracting as the industry price index falls. Initially, treated firms employed 6.7 percent of the workforce. After the reform, their employment share is 7.0 percent, i.e. an increase of 4.5 percent. Our quantitative analysis indicates that both small and large firms are affected by the reform. There is no clear relationship between initial market share and subsequent employment growth.

Industry-level results. Moving to the industry-level, we find that output per worker increases by up to three percent. The labor productivity gains are concentrated in industries where treated firms have an initially large market share, i.e. in those sectors where many firms experienced alleviated credit constraints due to the reform. Figure 2 documents the relationship between the percentage change in output per worker by industry, $\hat{Y}_s/\hat{L}_s$, and the market share of treated firms in the respective industry.

Sources of labor productivity growth: Recall that the change in industry labor productivity is given by $\hat{Y}_s/\hat{L}_s = T\hat{F}P_s \left(\hat{K}_s/\hat{L}_s\right)^{\alpha}$. 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, our analysis shows that the change in TFP is relatively small, and typically of an order of magnitude lower than the change in labor productivity. We also find that TFP declines for some industries, suggesting that financial frictions are also high for firms in the control group (see discussion in Section III.A and Section II.H for evidence). The quantitative results indicate that the main source of labor productivity growth in the aftermath of the collateral reform was capital deepening, i.e. that constrained firms invested more and therefore became more capital intensive (in intangible or tangible capital), while improved allocation within industries appears to have played a negligible role.

Aggregate gains. Finally, we quantify the aggregate gains from relaxing the collateral constraint using equations (21) and (22). By computing the initial

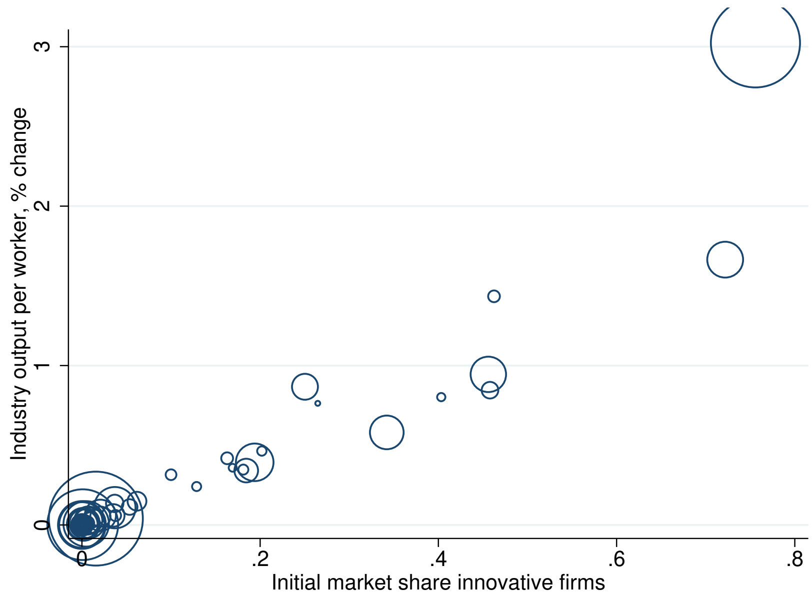


FIGURE 2. INDUSTRY OUTPUT PER WORKER, % CHANGE.

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

observed industry expenditure shares, θ_s, and using the quantified industry level results on labor productivity, we obtain $\hat{Y} = 1.006$. Multiplying this by the 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.

Back-of-the-envelope. For comparison, we also perform a back-of-the-envelope exercise that does not rely on the full model. The total implicit cost savings from removing the collateral constraint can then be expressed as $iK^{TR}(\tau - \tau') = iK^{TR}\tau'(1/\hat{\tau} - 1)$, where K^{TR} is the initial aggregate capital stock for treated firms and i is the interest rate. According to our data, the median bank interest rate is $i = 0.07$ during the period of observation, and the median change in credit constraints is $\hat{\tau} = 0.89$ (see above). The new level of constraints τ' is unobserved, but for the purposes of this exercise we assume that the credit friction is completely eliminated, i.e. $\tau' = 1$. 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.

Magnitudes. Is the quantified gain that arose over a three year period a small or large number? As 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 for allocation and productivity growth, and productivity-friendly regulation as an attractive alternative to government subsidies.

IV. Concluding Remarks

We investigate the effect of improved access to collateral, and thus reduced financial constraints, for firms holding patents. We find that improved access to collateral allowed innovating firms to increase their capital stock, while their marginal revenue product of capital declined. Our empirical results show that the increase in capital was enabled through improved access to credit reflected in a significant positive effect on the probability of getting bank loans, an increase in bank debt, reduced share of short term debt, and an increase in the number of bank connections.

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 these gains were concentrated in the sectors in the economy dominated by patenting firms. The economic magnitude of the gains is substantial and is primarily driven by capital deepening, whereas within-industry misallocation plays a smaller role.

The results suggest that policies enhancing the pledgeability of intangible capital are crucial in alleviating financial constraints for innovating firms for whom patents represent a key intangible asset. These firms are central drivers of innovation, and our results underscore the importance of regulation as a means of promoting innovation and productivity growth.

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Appendix

Solving the Model

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

Sales. Firm-level sales are

$$\begin{aligned} S_i &= (p_i/P_s)^{1-\sigma}\,\theta_s S \\ &= \left(\frac{\sigma}{\sigma-1}\kappa r_i^{\alpha} w^{1-\alpha}\right)^{1-\sigma} A_i^{\sigma-1} P_s^{\sigma-1}\theta_s S, \end{aligned} \tag{B1}$$

where S is aggregate sales across all industries.

Market shares. Sales of firm i relative to total sales in the industry s is

$$\begin{aligned} \omega_i &= \frac{S_i}{\sum_{i=1}^{M_s} S_i} \\ &= \frac{A_i^{\sigma-1} r_i^{\alpha(1-\sigma)}}{\sum_{j=1}^{M_s} A_j^{\sigma-1} r_j^{\alpha(1-\sigma)}}. \end{aligned} \tag{B2}$$

Employment. $(1-\alpha)$ is the firm's labor share, i.e. $(1-\alpha) = wL_i/Costs_i$, and sales are a mark-up over costs, $S_i = [\sigma/(\sigma-1)]\,Costs_i$. Combining those expressions and solving for L_i yields

$$\begin{aligned} L_i &= (1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}S_i \\ &= (1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}\left(\frac{\sigma}{\sigma-1}\kappa r_i^{\alpha}w^{1-\alpha}\right)^{1-\sigma}A_i^{\sigma-1}P_s^{\sigma-1}\theta_s S. \end{aligned} \tag{B3}$$

It follows that employment in industry s is

$$\begin{aligned} L_s &= \sum_{i=1}^{M_s} L_i = \sum_{i=1}^{M_s}(1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}S_i \\ &= (1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}\theta_s S. \end{aligned} \tag{B4}$$

Capital. The firm specific capital-labor ratio is

$$\frac{K_i}{L_i} = \frac{\alpha}{1-\alpha}\frac{w}{r_i}, \tag{B5}$$

Firm-level capital is therefore

$$K_i = \alpha\frac{\sigma-1}{\sigma}\left(\frac{\sigma}{\sigma-1}\kappa w^{1-\alpha}\right)^{1-\sigma}A_i^{\sigma-1}r_i^{\alpha(1-\sigma)-1}P_s^{\sigma-1}\theta_s S. \tag{B6}$$

The industry s capital stock is

$$\begin{aligned} K_s &= \sum_{i=1}^{M_s}\frac{\alpha}{1-\alpha}\frac{w}{r_i}L_i \\ &= \frac{\alpha}{1-\alpha}w\sum_{i=1}^{M_s}\frac{1}{r_i}(1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}S_i \\ &= \alpha\frac{\sigma-1}{\sigma}\sum_{i=1}^{M_s}\frac{1}{r_i}S_i \\ &= \alpha\theta_s\frac{\sigma-1}{\sigma}S\sum_{i=1}^{M_s}\omega_i\frac{1}{r_i}, \end{aligned} \tag{B7}$$

where ω_{si} is the industry sales shares, $\omega_i = S_i/\sum_{i=1}^{M_s}S_i$.

Labor productivity. Firm-level labor productivity is

$$\begin{aligned}\frac{Y_i}{L_i} &= \frac{S_i/p_i}{(1-\alpha)\,S_i\frac{\sigma-1}{\sigma}\frac{1}{w}}\\ &= \frac{\sigma}{\sigma-1}\frac{1}{1-\alpha}wp_i^{-1}\\ &= w\frac{1}{1-\alpha}A_i\left(\kappa r_i^{\alpha}w^{1-\alpha}\right)^{-1}.\end{aligned} \tag{B8}$$

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

$$\begin{aligned}\frac{Y_s}{L_s} &= \frac{\theta_s S/P_s}{(1-\alpha)\frac{\sigma-1}{\sigma}\frac{1}{w}\theta_s S}\\ &= \frac{1}{1-\alpha}\frac{\sigma}{\sigma-1}\frac{w}{P_s}.\end{aligned} \tag{B9}$$

Comparative Statics

We proceed by deriving the change in equilibrium outcomes. Recall that we focus on a relative change in firm-level credit constraints $\hat{\tau}_i$

Using equations (B1), (B3) and (B6), the relative changes in firm sales, employment and capital stock are

$$\begin{aligned}\hat{S}_i &= \hat{r}_i^{\alpha(1-\sigma)}\hat{P}_s^{\sigma-1}\\ \hat{L}_i &= \hat{r}_i^{\alpha(1-\sigma)}\hat{P}_s^{\sigma-1}\\ \hat{K}_i &= \hat{r}_i^{\alpha(1-\sigma)-1}\hat{P}_s^{\sigma-1}.\end{aligned}$$

The change in the capital CES price index is

$$\begin{aligned}\hat{r}_i &= \frac{\left(\left(\tau_I'\tilde{p}_I'\right)^{1-\psi}+\left(\tau_F'\tilde{p}_T'\right)^{1-\psi}\right)^{1/(1-\psi)}}{\left(\left(\tau_I\tilde{p}_I\right)^{1-\psi}+\left(\tau_F\tilde{p}_T\right)^{1-\psi}\right)^{1/(1-\psi)}}\\ &= \left(\frac{\left(\tau_I\tilde{p}_I\right)^{1-\psi}}{\left(\tau_I\tilde{p}_I\right)^{1-\psi}+\left(\tau_T\tilde{p}_T\right)^{1-\psi}}\left(\hat{\tau}_I\hat{\tilde{p}}_I\right)^{1-\psi}+\frac{\left(\tau_T\tilde{p}_T\right)^{1-\psi}}{\left(\tau_I\tilde{p}_I\right)^{1-\psi}+\left(\tau_T\tilde{p}_T\right)^{1-\psi}}\left(\hat{\tau}_T\hat{\tilde{p}}_T\right)^{1-\psi}\right)^{1/(1-\psi)}\\ &= \left(\xi_i\left(\hat{\tau}_I\hat{\tilde{p}}_I\right)^{1-\psi}+(1-\xi_i)\left(\hat{\tau}_T\hat{\tilde{p}}_T\right)^{1-\psi}\right)^{1/(1-\psi)},\end{aligned}$$

where ξ_i is the share of intangible spending in total capital spending:

$$\xi_i = \frac{I_i \tilde{p}_I}{r_i K_i} = \frac{\left(\frac{\tau_{Ii}\tilde{p}_I}{r_i}\right)^{1-\psi} r_i K_i}{r_i K_i} = \left(\frac{\tau_{Ir}\tilde{p}_I}{r_i}\right)^{1-\psi} = \frac{(\tau_{Ii}\tilde{p}_I)^{1-\psi}}{(\tau_{Ii}\tilde{p}_I)^{1-\psi} + (\tau_{Ti}\tilde{p}_T)^{1-\psi}}.$$

The change in the sector price index is

$$\begin{aligned}
\hat{P}_s^{1-\sigma} &= \frac{\sum_{i=1}^{M_s} (p_i')^{1-\sigma}}{\sum_{i=1}^{M_s} p_i^{1-\sigma}} \\
&= \frac{\sum_{i=1}^{M_s} A_i^{\sigma-1} (r_i')^{\alpha(1-\sigma)}}{\sum_{i=1}^{M_s} A_i^{\sigma-1} r_i^{\alpha(1-\sigma)}} \\
&= \sum_{i=1}^{M_s} \omega_i \hat{r}_i^{\alpha(1-\sigma)},
\end{aligned}$$

which yields the expression in equation (16) in the main text (when $\hat{r} = 1$).

The change in the capital allocated to industry s is

$$\begin{aligned}
\hat{K}_s &= \frac{\alpha\theta_s \frac{\sigma-1}{\sigma} S' \sum_{i=1}^{M_s} \omega_i \frac{1}{r_i'}}{\alpha\theta_s \frac{\sigma-1}{\sigma} S \sum_{j=1}^{M_s} \omega_j \frac{1}{r_j}}, \\
&= \sum_{i=1}^{M_s} \frac{\omega_i \frac{1}{r_i}}{\sum_{j=1}^{M_s} \omega_j \frac{1}{r_j}} \frac{1}{\hat{r}_i} \\
&= \sum_{i=1}^{M_s} \zeta_i \hat{r}_i^{-1},
\end{aligned}$$

where $\zeta_i = \frac{K_i}{\sum_{j=1}^{M_s} K_j}$ and we used the fact that $\frac{\omega_i/r_i}{\sum_j \omega_j/r_j} = \frac{S_i/r_i}{\sum_j S_j/r_j} = \frac{K_i}{\sum_j K_j}$.

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 $\hat{Y}_s = T\hat{F}P_s \hat{K}_s^{\alpha} \hat{L}_s^{1-\alpha}$. We have already derived expressions for $\hat{Y}_s$, $\hat{K}_s$ and $\hat{L}_s$. We insert these expressions and solve for

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

$$\left[\sum_{i=1}^{M_s} \omega_i \hat{r}_i^{\alpha(1-\sigma)}\right]^{1/(\sigma-1)} = T\hat{F}P_s \left(\sum_{i=1}^{M_s} \zeta_i \hat{r}_i^{-1}\right)^{\alpha}$$

$$T\hat{F}P_s = \frac{\left[\sum_{i=1}^{M_s} \omega_i \hat{r}_i^{\alpha(1-\sigma)}\right]^{1/(\sigma-1)}}{\left[\frac{1}{\bar{r}} \sum_{i=1}^{M_s} \zeta_i \hat{r}_i^{-1}\right]^{\alpha}},$$

which yields the expression in equation (19) in the main text.

Additional results

Table D1—Patent bins

	Bank loan dummy	Bank debt	Capital	1/MRPK	Intangible capital
	(1)	(2)	(3)	(4)	(5)
$Post2015 \times PatBin_i = 1$	0.042*	0.569***	0.432**	0.225**	1.660***
	(0.025)	(0.214)	(0.209)	(0.093)	(0.392)
$PatBin_i > 1$	0.063**	0.640**	0.109	-0.248*	-0.160
	(0.028)	(0.264)	(0.089)	(0.137)	(0.194)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	683,342	463,510	675,030	663,382	108,371

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, and a dummy for public funding, all interacted with year dummies. With capital and intangible capital as outcome we add an extra control variable to account for different accounting rules. 1/MRPK is measured by total fixed assets divided by operating income. $^{*}\, p < 0.1$, $^{**}\, p < 0.05$, $^{***}\, p < 0.01$.

Table D2—Robustness: Removing patent value from the measure of intangible intensity

	Bank loan dummy	Bank debt	Capital	1/MRPK	Intangible capital
	(1)	(2)	(3)	(4)	(5)
$Post2015 \times Pat_i$	0.063***	0.645***	0.209**	0.244***	1.440***
	(0.020)	(0.190)	(0.089)	(0.089)	(0.301)
Firm FE	Yes	Yes	Yes	Yes	Yes
Controls*year	Yes	Yes	Yes	Yes	Yes
Industry*year FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	PPML	PPML	OLS	PPML
Observations	747,738	492,422	747,423	725,587	111,385

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 excluding the value of patents, copyright and licenses, and a dummy for public funding, all interacted with year dummies. With capital and intangible capital as outcome we add an extra control variable to account for different accounting rules. 1/MRPK is measured by total fixed assets divided by operating income. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.