Financial Development and Labor Market Outcomes: Evidence from Brazil*

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March, 2021

Abstract

We estimate the effect of increased access to bank credit on the employment and wages of high- and low-skilled workers. To do so, we consider a bankruptcy reform that led to an expansion of bank credit to Brazilian firms. We use administrative data and exploit cross-sectional variation in the enforcement of the new legislation arising from differences in the congestion of civil courts. We find that the credit expansion led to an increase in the skill intensity of firms and in within-firm returns to skill, and to a reallocation of skilled labor from financially unconstrained firms to constrained firms. To rationalize these findings, we design a model in which heterogeneous producers face constraints in their ability to borrow and have production functions featuring capital-skill complementarity. We use this framework to generate an industry-level measure of capital-skill complementarity, which we use to provide direct evidence that the effect of access to credit on skill utilization and the skill premium is driven by a relative complementarity between capital and labor.

JEL Codes: G32; J21; J24; J31

Keywords: Financial constraints; Human capital; Labor misallocation

*Julia Fonseca is grateful to Atif Mian, Mark Aguiar, Will Dobbie, and Motohiro Yogo for their continued guidance and support, and to Adrien Matray for invaluable advice throughout this project. The authors would also like to thank Leah Boustan, Giulia Brancaccio, Markus Brunnermeier, Victor Duarte, Maryam Farboodi, Sergio Lago, André Minella, Ben Moll, Steve Redding, Clara Santamaria, David Schoenherr, Molly Schnell, Arlene Wong, Wei Xiong, Owen Zidar, and numerous seminar participants for helpful comments. This research received financial support from the NBER Household Finance small grant program and from the Becker Friedman Institute through its Macro Financial Modeling Initiative. The views in this paper are those of the authors and do not reflect the opinions of the Central Bank of Brazil.

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1 Introduction

Financial constraints are a pervasive characteristic of low- and middle-income economies. In Brazil, for instance, 45% of firms identify access to finance as a major constraint (2009 World Bank Enterprise Survey). Extensive literature has found that financial frictions affect economic development not only by slowing capital accumulation but also by causing capital to be misallocated across producers.[1] Because there is complementarity between capital and labor, these findings suggest a role for the cost and availability of external finance in determining labor market outcomes. Moreover, financial frictions can also impact the skill composition of a firm's workforce, as well as the returns to skill, as skilled and unskilled labor potentially differ in how complementary they are to capital.

This paper sheds light on the effect of increased access to bank credit on the employment and wages of high- and low-skilled workers. To conduct our analysis, we assemble a comprehensive firm-level panel of formally registered Brazilian firms using matched employer-employee data, credit registry data, and data on real outcomes such as assets, investment, and output. Our identification strategy makes use of a 2005 reform to the legislation governing bankruptcy proceedings in Brazil, which significantly strengthened the rights of secured creditors and led to an increase in the borrowing capacity of firms.

To identify the impact of the 2005 bankruptcy reform and subsequent credit expansion on labor market outcomes, we exploit cross-sectional variation in the enforcement of the new legislation arising from differences in the congestion of civil courts (Ponticelli and Alencar, 2016). We start by showing that the 2005 bankruptcy reform significantly increased firm-level access to bank credit. We find that the growth in bank credit is 7.4 percentage points

[1] Early work includes King and Levine (1993), Jayaratne and Strahan (1996), and Rajan and Zingales (1998). For studies on the impact of financial frictions on capital accumulation, see also Levine and Zervos (1998) and Rioja and Valev (2004). See, for instance, Bertrand, Schoar, and Thesmar (2007), Buera, Kaboski, and Shin (2011), Moll (2014), Cong et al. (2019), Catherine et al. (2017), and Bai, Carvalho, and Phillips (2018) for studies on the impact of financial frictions on the allocation of capital.

higher for firms in high-enforcement localities relative to firms in low-enforcement localities following the reform.

Our research has three main sets of empirical results. First, we find that increased access to credit causes firms to increase their skill intensity. In particular, we find that the growth in the share of skilled workers is 4.0 percentage points higher for firms in high-enforcement localities relative to firms in low-enforcement localities after the reform, with skill defined as educational attainment. We also observe an increase in employment in occupations that are intensive in nonroutine cognitive tasks. These findings suggest that access to credit allows firms to hire and retain more skilled workers and workers who are not easily replaceable by machinery and equipment.

Second, we find that increased access to credit leads to an increase in the within-firm return to skill. Specifically, we find that firms in high-enforcement localities experience 3.8 percentage points higher growth in the skill premium relative to firms in low-enforcement localities. This suggests that access to credit impacts not only the relative quantity of skilled labor but also its relative price, thus affecting within-firm earnings inequality.

What can explain the observed increase in the relative utilization of skill and the return to skill following a credit expansion? One possibility is that capital and skilled labor are relative complements. If that is the case, an increase in capital accumulation will cause skilled labor to become more productive relative to unskilled labor. This in turn will lead to an increase in the employment of skilled workers relative to unskilled workers and/or an increase in the skill premium.

Our third set of empirical findings sheds light on the mechanism behind the effect of access to credit on skill intensity and the skill premium. We find that firms in high-enforcement localities increase their level of investment following the expansion in credit, relative to firms in low-enforcement localities. Moreover, we provide direct evidence in favor of the capital-skill complementarity channel by exploiting variation in the degree of capital-skill complementarity at the industry level. We find that treated firms in high-complementarity industries increase their utilization of skilled labor and their within-firm returns to skill by more than treated firms in low-complementarity industries. In this set of results, we can flexibly control for any unobserved time-varying differences between localities, alleviating concerns that our findings are driven by local economic conditions or other regional differences.

To rationalize these findings, we design a model in which heterogeneous producers face constraints in their ability to borrow (Moll, 2014) and technology is such that skilled labor is more complementary to capital than unskilled labor. Production functions have a nested CES form and feature capital-skill complementarity as in Krusell et al. (2000). In the presence of capital-skill complementarity, an increase in capital will cause the productivity of skilled workers to increase by more than the productivity of unskilled workers. These theoretical predictions are in line with the observed increase in investment, the employment of skilled workers, and the skill premium, as long as we assume a relative complementarity between capital and skilled labor.

To provide direct evidence in favor of the capital-skill complementarity assumption, we estimate production function parameters for each 2-digit industry and compute the elasticities of substitution between unskilled labor and capital and between skilled labor and capital. Our estimation procedure involves first estimating a second-order approximation of the production function as in De Loecker and Warzynski (2012). In a second step, we use these reduced-form estimates to recover the structural parameters of our nested CES production function using a minimum distance estimation procedure. We find that all industries in manufacturing and extractive sectors display some degree of capital-skill complementarity.[2] This is in line with previous work that sought to quantify the degree of capital-skill complementarity in different industries (Larrain, 2015).

[2] We are only able to estimate production function parameters for industries in manufacturing and extractive sectors as this estimation procedure requires data on value added and capital, which are only available for firms in these sectors.

Another theoretical prediction that arises from our model is that financially constrained firms should experience larger employment effects as a consequence of the bankruptcy reform and the subsequent expansion of bank credit. We take this prediction to the data using firm size and firm age as proxies for financial constraints (Hadlock and Pierce, 2010). According to both measures of financial constraints, the share of skilled workers rises more at financially constrained firms in high-enforcement localities than in unconstrained firms in high-enforcement localities. Further, we find that the rise in the share of skilled workers at constrained firms is entirely driven by skilled workers previously employed at an unconstrained firm, suggesting that constrained firms are able to poach skilled workers from their unconstrained competitors after the reform. This indicates that increased access to bank credit impacts not only the overall level of skill utilization but also the allocation of skill, with resources shifted toward financially constrained firms. As in the analysis that exploits industry-level variation in the degree of capital-skill complementarity, we can include locality-time fixed effects in these specifications. This is thus another set of results suggesting that our findings are not driven by any unobservable time-varying differences across localities.

In addition to ruling out differences in local economic conditions as the driving force behind our results, we confirm the robustness of our empirical findings to flexibly controlling for industry-specific trends. This alleviates concerns that our results are biased by differential firm growth across product categories. We also control for pre-existing differences in the share of skilled workers across firms, suggesting that our results are not driven by a disproportionate increase in borrowing and investing by skill-intensive firms. Finally, while it is the case that financially constrained firms experience larger employment effects as a consequence of the 2005 reform, we show that our results are robust to controlling for proxies for funding needs.

Overall, our results add to a growing body of evidence supporting the existence of an important link between financial frictions and labor markets. Moreover, our findings suggest that by introducing distortions in the allocation of capital, financial frictions lead to distortions in the allocation of skill. We thus provide new evidence on the specific channels through which financial development can improve the allocation of production factors and hence increase aggregate productivity.

Our work contributes to the recent literature on the impact of financial frictions on long-term labor market outcomes. For instance, Bai, Carvalho, and Phillips (2018) and Caggese, Cunat, and Metzger (2019) find that financial frictions impact firm-level employment decisions, with consequences for the allocation of labor across producers as well as aggregate unemployment rates. We add to this literature by providing evidence that access to external finance impacts the types of workers a firm employs, in terms of both educational attainment and occupation, as well as the within-firm returns to skill. Moreover, we provide direct evidence that the shift in skill intensity and the rise in the skill premium triggered by increased access to credit are at least partly driven by complementarities between capital and skill.

The present work is also connected to a rich body of literature in macroeconomics and finance that studies the impact of financial frictions on the allocation of capital across producers (Bertrand et al., 2007; Buera et al., 2011; Midrigan and Xu, 2014; Moll, 2014; Gopinath et al., 2017; Cong et al., 2019; Catherine et al., 2017; Bai et al., 2018; Bau and Matray, 2020; Matray and Boissel, 2020). We contribute to this literature in three ways. First, we provide causal, micro-level evidence of the effect of financial constraints on the allocation of both capital and labor in the context of a middle-income country. Second, we find that financial frictions affect not only investment and total employment but also the types of workers that a firm employs and the allocation of skill.

This paper also relates to the literature that estimates the effect of transient negative credit supply shocks on total employment (Peek and Rosengren, 2000; Chodorow-Reich, 2014; Greenstone et al., 2020; Duygan-Bump et al., 2015; Bottero et al., 2020; Huber, 2018; Benmelech et al., 2018). We complement this literature by shedding light on the characteristics of employees whose hiring and firing are impacted by a firm's access to credit. We also provide new evidence on the impact of access to bank credit on wages, demonstrating that gains are concentrated on skilled workers.

A small number of prior or concurrent studies within the literature on credit and employment focus on the heterogeneous effects of negative credit supply shocks on workers with different levels of educational attainment (Berton et al., 2018; Barbosa et al., 2020). We contribute to this work in three ways. First, we show direct evidence that skilled labor is reallocated from financially unconstrained firms to constrained firms, indicating that access to credit meaningfully impacts the allocation of skill. Second, we shed light on the mechanism behind the link between access to credit and the skill composition of firms and provide evidence that our results are driven by a relative complementarity between capital and skilled labor. Finally, we analyze the effect of a positive and persistent shock to bank credit in a middle-income country.

Finally, this paper is also related to previous work analyzing the 2005 Brazilian bankruptcy reform. Ponticelli and Alencar (2016) find that firms in localities with less-congested courts experienced a larger increase in credit, investment, and output following the reform. Our results are consistent with these findings and we add to this work by investigating the effect of the credit expansion triggered by the reform on the skill composition of firms, the within-firm returns to skill, and the allocation of skill, and by showing that these results are at least partly driven by capital-skill complementarity.

The remainder of this paper is structured as follows. Section 2 describes the data and the institutional features of the Brazilian bankruptcy reform. Section 3 develops the conceptual framework that guides our empirical work and describes our estimation procedure. Section 4 details our empirical strategy. Section 5 reports our main results and evaluates their robustness. Section 6 concludes.

2 Institutional setting and data

2.1 The 2005 bankruptcy reform in Brazil

Our empirical strategy uses the 2005 Brazilian bankruptcy reform as a source of exogenous variation in the availability of credit to firms. In this section, we describe the key features of the reform and discuss how these changes resulted in increased access to corporate credit. For a thorough discussion of the changes implemented by the new bankruptcy legislation, see Araujo and Funchal (2005).

The bankruptcy legislation that came into effect in Brazil in 2005 was the most consequential reform to the country's insolvency procedures since 1945, when the previous insolvency statute was enacted. The pre-2005 legislation was considered punitive to creditors and was criticized for contributing to Brazilian interest rate spreads ranking among the highest in the world.[3] The main issues with the existing legislation were: (i) the bankruptcy priority rule, which prioritized both labor claims and tax claims before of creditors; and (ii) what is generally referred to "successor liability" (Araujo, Ferreira, and Funchal, 2012). Successor liability meant that tax claims, labor claims, and all other liabilities were transferred to the buyer of an asset sold in liquidation which, according to anecdotal accounts, led to a depressed market value of the pool of bankruptcy assets. These issues resulted in an estimated rate of recovery in the event of insolvency of about 0.2% in 2004, which is extremely low even in comparison with other Latin American countries (World Bank Doing Business database).

Efforts to reform Brazilian bankruptcy laws started in 1993, with the goals of making legislation more creditor-friendly and increasing the recovery rate of creditors. The reform was seen as a crucial step toward reducing bank spreads and increasing the volume of private

[3] For instance, according to Paiva Muniz and Palhares Basilio (2005), "The inefficiency of [the prior] Brazilian insolvency rules ha[d] severe negative impacts on the economy, to the extent that they adversely affect[ed] the spread in the interest rates charged by financial institutions, which are among the highest in the world."

credit to corporations.[4] After several amendments, the reform package was approved by the House of Representatives in October 2003 and by the Senate in December 2004. The approved bill was signed into law in February 2005 and became effective 120 days later.

In this paper, we focus on two key aspects of the new legislation that introduced changes to the liquidation procedure. First, secured creditors were given priority over tax claims in the bankruptcy priority rule. Second, tax claims, labor claims, and other liabilities were no longer transferred to the buyer of an asset sold in liquidation. Fig. 1 shows the expected recovery rate estimated by the World Bank from 2004 to 2013. According to these estimates, the recovery rate increased sharply from about 0.2 in 2004 to 12.1 cents on the dollar in 2007, in line with what we would expect given the nature of the changes introduced by the new legislation.

As a consequence of higher rates of recovery, we expect an increase in the availability of credit. In Panel A of Fig. 2, we show that private credit expanded rapidly following the reform, from under 30% of GDP in 2004 to close to 63% in 2013. In all likelihood, this aggregate trend is partially attributable to a credit boom that was felt throughout the continent. But while Brazil was not the only Latin American country to experience a private credit expansion during the 2000s, Brazil's expansion seems to have surpassed those of other countries. We illustrate this in Panel B of Fig. 2 by also showing the evolution of credit other Latin-American countries.

2.2 Data sources

Our analysis uses data from four distinct sources. Matched employer-employee data come from the *Relação Anual de Informações* (RAIS), a mandatory survey completed annually by all tax-registered firms in Brazil. Incomplete or late information results in severe penalties,

[4] For instance, this argument was made by the then Minister of Finance, Antonio Palocci, in his inauguration speech, in January 2003 (http://www1.folha.uol.com.br/folha/dinheiro/ult91u61397.shtml)

which leads to a high degree of compliance and essentially complete coverage of all employees in the Brazilian formal sector. RAIS contains a time-invariant identifier for each worker as well as time-invariant firm identifiers. This allows us to link all workers to the firm that employs them and to follow a given worker over time. Importantly, this data set also has information on the geographical location of the firm, which we use to link it to data on judicial outcomes described below. We observe data on average gross monthly earnings and the average number of hours worked, as well as worker characteristics such as education, occupation, race, age, and gender. We restrict our attention to full-time workers at private-sector firms and use data at the firm-level from 2000 to 2010. Additionally, we restrict attention to firms with more than one employee to avoid the inclusion of individuals registered as firms.

Credit registry data are from the *Sistema de Informações de Créditos* (SCR) of the Central Bank of Brazil and are available from 2003 onward. This data set contains information on the geographical location of the firm, as well as time-invariant identifiers for each loan, bank, and firm, allowing us to track any corporate loan above 5,000 BRL granted by a financial institution operating in Brazil. This information is reported by banks to the Central Bank of Brazil and is of high quality because loan amounts reported to the credit registry must match banks' quarterly accounting figures. We collapse the data to the firm-quarter-year level and restrict attention to private-sector firms.

Data on judicial outcomes come from *Justiça Aberta*, a data set covering all Brazilian courts maintained by the National Justice Counsel. Data are collected through a mandatory survey completed monthly by judges and administrative staff of each court. This data set contains information on the number of cases and judges for all Brazilian courts, which we use to construct a court-level measure of congestion equal to the number of cases divided by the number of judges. We focus on first instance civil courts as these are the courts responsible for bankruptcy cases. We use information about the municipality in which courts are located to link these data with our other data sets. We also use this geographical information to merge in other municipality characteristics in the pre-reform period. These include local GDP per capita and population, which we obtain from the Brazilian Institute of Geography and Statistics (IBGE), the number of bank branches in a given locality, which we obtain from the ESTBAN database maintained by the Central Bank of Brazil, and population size from the 2000 Population Census.

Finally, firm-level data on real outcomes come from the *Pesquisa Industrial Anual da Empresa* (PIA), which is based on annual surveys completed by firms in the manufacturing and mining sector. The surveys are mandatory for all firms with 30 or more employees or above a certain revenue threshold (300,000 USD in 2012), and there are fines for noncompliance. The PIA data set also includes a random sample of firms with 5 to 29 employees, referred to as the "sampling stratum" (*estrato amostrado*). We restrict our analysis to the universe of larger firms, which are sampled with a probability of one, because we are unable to follow firms over time in the sampling stratum or observe information such as the municipality in which the firm is located. These data contain information on operational and nonoperational costs, revenues, assets, and investment, as well as time-invariant firm identifiers.

Panel A of Table 1 provides summary statistics of firm characteristics. Employment information comes from the RAIS dataset, credit information comes from SCR, and data on output and investment is from PIA. Note that, even though it is available at a quarterly frequency, the SCR data set has a similar number of observations as RAIS since it is only available from 2003 onward and for firms with bank loans above 5,000 BRL. The PIA dataset, in turn, has fewer observations as it only contains information on firms in manufacturing or mining sectors with at least 30 employees. Panel B of Table 1 reports descriptive statistics of geographical area characteristics in the pre-reform period, with one observation per geographical area. To account for the fact that municipality borders have changed over time, we use as our level of aggregation minimum comparable areas (Área Mínima Comparável, or AMC), which can be consistently compared throughout our sample period. During our sample period, Brazil had 4,620 AMCs.

3 Conceptual framework

In this section, we introduce a simple model in which firms face constraints in their ability to borrow, and production functions have a nested CES form featuring capital-skill complementarity as in Krusell et al. (2000).

The goal of the model is to shed light on how we should expect the 2005 bankruptcy reform to affect the employment and earnings of high- and low-skilled workers. We start by describing the model and then discuss the effect of loosening credit constraints on firms' employment and investment decisions in the context of the model.

3.1 Model

3.1.1 Preferences and Technology

The model has two periods, $t = 0, 1$. There is a continuum of entrepreneurs indexed by their productivity Z and their initial wealth A. Productivity and initial wealth are distributed uniformly and independently across entrepreneurs.

Each entrepreneur i owns a private firm that uses K_i units of capital, S_i hours of skilled labor, and N_i hours of unskilled labor at $t = 0$ to produce Q_i units of the final good at $t = 1$ according to the following production technology:

$$Q_i = F(Z_i, K_i, S_i, N_i) = Z_i \left(\nu N_i^\sigma + (1 - \nu)(\tau K_i^\rho + (1 - \tau) S_i^\rho)^{\frac{\sigma}{\rho}} \right)^{\frac{1}{\sigma}}. \tag{1}$$

This production function is a version of the technology in Krusell et al. (2000) without capital differentiation and, as in Krusell et al. (2000), there is capital-skill complementarity as long as $\sigma > \rho$.

Firms are monopolistically competitive, and each firm faces an isoelastic demand curve with a common elasticity of demand $\varepsilon > 1$.

3.1.2 Financial Markets

The only asset in this economy is productive capital. A perfectly competitive financial intermediary collects deposits and rents out capital to entrepreneurs. The return on deposited assets is r and the break-even condition of the intermediary implies that the rental price of capital is $r + \delta$, where δ is the rate at which capital depreciates.

The key friction in this market is limited enforcement. In period $t = 1$, an entrepreneur can steal a fraction $1 - \eta$ of rented capital K_i. As punishment, the entrepreneur would lose her wealth. The intermediary will then allow the entrepreneur to rent capital as long as the entrepreneur's incentive compatibility constraint is satisfied. This requires that

$$R_i K_i - (1 + r)(K_i - A_i) \geq R_i K_i - \eta K_i,$$

where R_i denotes the gross return to capital investment of entrepreneur i. This implies that an entrepreneur faces a collateral constraint given by

$$K_i \leq \lambda(r, \eta) A_i, \tag{2}$$

where

$$\lambda(r,\eta) \equiv \frac{1+r}{1+r-\eta}. \tag{3}$$

While simple, this formulation yields a tractable model of capital market imperfections that cause initial wealth to limit investment. Moreover, by varying η (and consequently λ), we are able to outline all degrees of capital-market efficiency. This formulation of a capital rental market in which entrepreneurs face collateral constraints is similar to that of Buera et al. (2013) and Moll (2014), and captures the intuition that the amount of capital available to an entrepreneur is limited by her personal assets (Kiyotaki and Moore, 1997).

3.1.3 Firm Optimization

Each entrepreneur faces the following profit maximization problem, which will determine her factor demands

$$\begin{aligned} \max_{P_i,Q_i,K_i,S_i,N_i} \quad & P_i(Q_i)Q_i(Z_i,K_i,S_i,N_i) - w_s S_i - w_n N_i - (r+\delta)K_i \\ \text{s.t.} \quad & K_i \leq \lambda(r,\eta)A_i. \end{aligned}$$

The first-order conditions with respect to skilled and unskilled labor for an active entrepreneur (i.e., an entrepreneur with production Q_i greater than zero) are, respectively

$$\begin{aligned} & w_s = (1-\nu)\left(\tau K_i^\rho + (1-\tau)S_i^\rho\right)^{\frac{\sigma-\rho}{\rho}} (1-\tau)S_i^{\rho-1}\left(1-\frac{1}{\varepsilon}\right)P_i Z_i^\sigma Q_i^{1-\sigma} \text{ and} \\ & w_n = \nu N_i^{\sigma-1}\left(1-\frac{1}{\varepsilon}\right)P_i Z_i^\sigma Q_i^{1-\sigma}. \end{aligned}$$

Through dividing one expression by the other and rearranging terms, we obtain the following equation for the skill premium

$$\frac{w_s}{w_n} = \frac{(1-\nu)(1-\tau)}{\nu}\left(\frac{N_i}{S_i}\right)^{1-\sigma}\left[\tau\frac{K_i}{S_i}^{\rho} + (1-\tau)\right]^{\frac{\sigma-\rho}{\rho}}. \tag{4}$$

3.2 Estimating Production Function Parameters

The key determinants of the response of employment and earnings of high- and low-skilled workers to a loosening of credit constraints in this model are the parameters governing the elasticities of substitution between unskilled labor, capital, and skilled labor (σ and ρ), as illustrated by Eq. (4). Accordingly, to use this framework to generate predictions about the impact of credit constraints on the skill composition and the skill premium, we use our firm-level PIA-RAIS sample from 2000 to 2010 to estimate these and other production function parameters. We are only able to estimate production function parameters for the PIA-RAIS sample as this estimation procedure requires data on value added and assets, which is only available in the PIA sample, as well as employment data from RAIS. As discussed in Section 2.2, this sample contains information for firms in manufacturing and extractive sectors. Moreover, in Section 5.3, we describe how we use these structural estimates to provide evidence that our empirical results are at least partly driven by the capital-skill complementarity channel.

Our estimation procedure consists of two steps. In the first step, we estimate an approximation of the production function in Eq. (1). Letting lower case variables represent logged upper case variables, a second-order approximation yields

$$q_i = \gamma_s s_i + \gamma_n n_i + \gamma_k k_i + \sum_{x\in\{s,n,k\}} \gamma_{xx} x_i^2 + \sum_{w\neq x}\sum_{x\in\{s,n,k\}} \gamma_{xw} x_i w_i + z_i, \tag{5}$$

where

$$\gamma_k = (1-\nu)\tau \tag{6}$$

$$\gamma_n = \nu \tag{7}$$

$$\gamma_s = (-1+\nu)(-1+\tau) \tag{8}$$

$$\gamma_{kk} = -\frac{((-1+\nu)^2(-1+\sigma)\tau^2)}{2} + \frac{(-1+\nu)\tau(-\rho+\rho\tau-\sigma\tau)}{2} \tag{9}$$

$$\gamma_{nn} = \frac{\nu^2+\nu\sigma-\nu^2\sigma}{2} \tag{10}$$

$$\gamma_{ss} = \frac{(-1+\nu)^2(-1+1/\sigma)(-\sigma+\sigma\tau)^2}{2\sigma} - \frac{(-1+\nu)(\sigma^2+\rho\sigma\tau-2\sigma^2\tau-\rho\sigma\tau^2+\sigma^2\tau^2)}{2\sigma} \tag{11}$$

$$\gamma_{kn} = (-1+\nu)\nu(-1+\sigma)\tau \tag{12}$$

$$\gamma_{ks} = (-1+\nu)\tau(-1+\nu+\rho-\nu\sigma+\tau-\nu\tau-\rho\tau+\nu\sigma\tau) \tag{13}$$

$$\gamma_{sn} = (1-\nu)\nu(-1+\sigma)(-1+\tau)), \tag{14}$$

Our preferred method follows De Loecker and Warzynski (2012) and estimates Eq. (5) separately for each 2-digit industry relying on proxy methods developed by Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) to control for unobserved productivity shocks, which are potentially correlated with input choices. More specifically, we proxy for productivity using the demand for materials and follow Ackerberg et al. (2015) in estimating all production function parameters using second-stage moments. From this step, we obtain estimates of the coefficients in Eq. (5) as well as estimates of markups. We discuss the details of this production function estimation procedure in Appendix A.

In a second step, we use reduced-form estimates of the coefficients in Eq. (5) to recover the structural parameters of Eq. (1) using a minimum distance estimation procedure. Let $\theta = \{\nu,\ \tau,\ \sigma,\ \rho\}$ represent the vector of structural parameters and $\gamma = h(\theta)$ represent the nonlinear system of Eqs. (6)–(14). With an estimate $\hat{\gamma}$ of the coefficients in Eq. (5)

obtained in the first step of our estimation procedure, we compute an efficient minimum distance estimator of the vector of structural parameters θ by solving

$$\min_{\theta \in \Theta} \{\hat{\gamma} - h(\theta)\}' \hat{\Xi}^{-1} \{\hat{\gamma} - h(\theta)\}, \tag{15}$$

where $\hat{\Xi}$ is the variance-covariance matrix of the reduced-form coefficients obtained in the first step of our estimation procedure. This 2-step estimation procedure produces estimates of production function parameters for each 2-digit industry.

In Table 2, we report estimates of the parameters governing the elasticities of substitution between inputs (σ and ρ) and of the parameters governing income shares (ν and τ) for each sector. We find that $\sigma > \rho$ for all 2-digit industries, suggesting that all industries in manufacturing and extractive sectors display some degree of capital-skill complementarity. This result is consistent with previous work that finds evidence of capital-skill complementarity for all industries in manufacturing using US data (Larrain, 2015).

3.3 The Effect of Loosening Credit Constraints

In Section 2.1, we argued that the 2005 bankruptcy reform increased the recovery rate of creditors. Through the lens of our model, this can be interpreted as an increase in the recovery rate η. From Eq. (3), this implies an increase in the maximum leverage rate λ, that is, a relaxation of the credit constraint modeled in Eq. (2). For that reason, it will be useful to consider the implications of an increase in λ in the context of our model.

Intuitively, a constrained entrepreneur sees a direct increase in her ability to rent capital as a result of looser credit constraints. Assuming the constraint binds for at least some firms, we should then expect an increase in capital accumulation and borrowing (given by $K - A$ in the model) following the reform.

Note that the maximum leverage rate λ has no direct effect on either skilled or unskilled labor in our model. However, labor is still impacted by the effect of looser credit constraints on capital. More specifically, an increase in capital raises the marginal productivity of labor which, all else being equal, increases the demand for labor.

The model also has implications for the ratio of skilled to unskilled hours (S/N) and for the skill premium (w_s/w_n). Rearranging terms on Eq. (4), we obtain

$$\frac{w_s}{w_n}\left(\frac{S}{N}\right)^{1-\sigma} = \frac{(1-\nu)(1-\tau)}{\nu}\left[\tau\frac{K}{S}^{\rho} + (1-\tau)\right]^{\frac{\sigma-\rho}{\rho}}.$$

Under capital-skill complementarity ($\sigma > \rho$), consistent with the estimates we obtain in Section 3.2, an increase in the stock of capital relative to skilled hours leads to an increase in the skill premium, an increase in the ratio of skilled to unskilled hours, or both. Intuitively, if capital is relatively more complementary to skilled labor, the marginal productivity of skilled labor rises by more than the marginal productivity of unskilled labor when capital utilization increases. This increase in relative productivity leads to an adjustment in quantities (the skill composition), in prices (the skill premium), or both.

4 Research design

Our identification strategy uses the 2005 Brazilian bankruptcy reform as plausibly exogenous variation in the recovery rate of lenders and, consequently, in the availability of credit to firms. To identify the causal effect of increased access to credit, we exploit cross-sectional variation in the congestion of civil courts. In this section, we first discuss our empirical strategy and then describe how we measure court congestion in the data.

4.1 Empirical Strategy

We estimate the effect of increased access to credit using the 2005 Brazilian bankruptcy reform as a quasi-natural experiment and employing a difference-in-differences research design, in which we compare outcomes for firms who were more exposed to the reform (the "treatment" group) and firms that were less exposed (the "control" group), before and after the reform. Our variation in exposure to the reform arises from cross-sectional variation in the congestion of civil courts. Intuitively, creditors in localities with less congested courts should be better positioned to reap the benefits of the reform, as more-efficient courts are better able to enforce the new legislation (Ponticelli and Alencar, 2016). This suggests that the recovery rate of creditors in localities with less congested courts should increase by more than that of other creditors.

The framework of Section 3 implies that a relative increase in the recovery rate of creditors should lead to looser credit constraints, directly increasing the borrowing capacity of firms. This relative increase in borrowing capacity should lead to higher investment which, under the assumption of capital-skill complementarity, should lead to an increase in the relative utilization of skill, in the skill premium, or both.

The role of the control group is to provide a counterfactual of what would have happened to firms' outcomes if this legislation had not been implemented. Accordingly, the identifying assumption is that, in the absence of the 2005 bankruptcy reform, outcomes for treatment and control firms would have maintained parallel trends. Our main approach to assess the validity of this assumption is to examine outcomes for firms in the treatment and control groups in the pre-reform period. As we discuss in Section 5, our estimates show that outcomes for the two groups move in close parallel prior to the reform. We take these results as evidence that our control group establishes an accurate counterfactual for what would have happened to the treatment group in the absence of the reform.

Our baseline specification consists of a difference-in-differences specification of the form

$$g(Y_{icst}) = \beta_1 Reform_t \times HighEnforcement_c + \beta_2 X_{it} + \kappa_i + \theta_{st} + \epsilon_{icst}, \tag{16}$$

where $g(Y_{icst})$ is the growth rate in the outcome of interest for firm i in locality c in state s between the years $t-1$ and t; $Reform_t$ is a dummy that equals zero prior to the reform and one after the reform, $HighEnforcement_c$ is a dummy for firm i being in a locality c with below-median court congestion; X_{it} is a set of controls; κ_i is a vector of firm fixed effects; θ_{st} is a vector of state-year fixed effects. Our coefficient of interest β_1 represents the average within-firm change in our outcome variables for firms in localities with low court congestion relative to firms in high-congestion localities, following the 2005 bankruptcy reform.

We compute growth rates using the Davis and Haltiwanger (1992) growth measure

$$g(Y_{it}) = \frac{Y_{it} - Y_{it-1}}{\frac{1}{2}\left(Y_{it} + Y_{it-1}\right)}. \tag{17}$$

We opt for this measure of growth rates due to its useful statistical properties, such as symmetry around zero and boundedness in the range $[-2, 2]$, and to the fact that it leads to estimates that are easy to interpret and compare.[5] As a robustness check, we show estimates with dependent variables in logs in Appendix Table B6 and are reassured to find that results are qualitatively identical.

To provide evidence in favor of the parallel trends assumption discussed above, we also estimate equations of the following form

[5] For further details on the advantages of this growth measure, we refer the reader to Davis and Haltiwanger (1992).

$$g(Y_{icst}) = \sum_{\tau \in \mathcal{T}} \beta_\tau I(\tau) \times HighEnforcement_c + \gamma X_{it} + \kappa_i + \theta_{st} + \epsilon_{icst}, \quad (18)$$

where $I(\tau)$ is a dummy equal to one exactly τ years after (or before if τ is negative) the reform.

4.2 Measuring Court Congestion

In Section 4.1, we argue that less congested courts are better able to enforce the 2005 bankruptcy reform and, consequently, firms in localities with less congested courts are differentially exposed to the new legislation. We follow Ponticelli and Alencar (2016) and measure court congestion in a given court as the total number of pending cases divided by the number of judges working in that court. For municipalities that have a specialized bankruptcy court, we assign the congestion measure of that court to the municipality. For all other municipalities, we measure congestion as the average congestion of all courts of first instance, weighted by the number of pending cases in each court. We focus on courts of first instance as these are the courts responsible for bankruptcy cases in the absence of specialized courts.

To account for the fact that municipality borders can and have changed over time, we conduct our analysis at the minimum comparable area (Área Mínima Comparável, or AMC) level, an aggregation level that can be consistently compared over time. In 2010, Brazil had 5,565 municipalities, which could be matched to 4,620 AMCs and, throughout the text, we use the terms AMC and locality interchangeably. We measure court congestion at the AMC level as the weighted average of congestion across municipalities in the same AMC, using the population in each municipality as weights.

We define a locality as "high enforcement" ($HighEnforcement_i = 1$ in Equation 16) if its level of court congestion is below the median. As mentioned in Section 2, judicial variables are available from 2009 onward. Accordingly, we measure court congestion in January 2009 and use it as a time-invariant proxy for enforcement. In Table 3, we report differences in characteristics of high- and low-enforcement localities in the pre-reform period. Firms in high- and low-enforcement localities have a similar number of employees and a similar share of managers, pay a similar premium for skill, and have similar levels of investment and borrowing. High- and low-enforcement localities also have a similar level of GDP per capita, a similar share of manufacturing in local value added, and a similar number of bank branches.

The only statistically significant difference between firms in high- and low-enforcement localities that we observe in Table 3 is in the share of skilled workers. Note that a level difference in the share of skilled workers is not a threat to our identification strategy as long as there are no differences in the trend of outcomes of treated and control firms, and we provide evidence in favor of the parallel trends assumption in Section 5 However, we include the share of skilled workers prior to the reform (interacted with the $Reform_t$ dummy) as a control in our baseline specification, to alleviate potential concerns that our results are driven by a disproportionate increase in borrowing and investing by skill-intensive firms.

5 Results

5.1 Effect on credit, employment, and investment

We start by providing evidence that the 2005 bankruptcy reform led to an increase in credit for firms in high-enforcement localities relative to firms in low-enforcement localities. Establishing this result is crucial to our identification strategy because we use the bankruptcy reform as a quasi-natural experiment that led to increased credit availability to firms. We do so by estimating Eq. (16) with bank credit growth as the dependent variable. We define bank credit as the sum of all existing loans granted by any financial institution to a given firm at a point in time.

The specification in Eq. (16) estimates how access to bank credit changed after the reform for firms in localities with less congested courts—and thus higher enforcement of the bankruptcy reform—relative to firms in localities with more-congested courts. All specifications include firm fixed effects to account for any level differences between these groups of firms, as well as state×time fixed effects to flexibly control for any time trends common to all firms in a given state. Standard errors are clustered at the locality level throughout.

Column 1 of Table 4 shows that bank credit growth is higher for firms in high-enforcement localities relative to firms in low-enforcement localities following the reform. In column 2 of Table 4, our preferred specification, we add a series of controls to capture potential differences in economic and financial development at the locality level. These include local GDP per capita, the share of manufacturing in local value added, and the number of bank branches per 100,000 people. We measure these variables in 2004, the year before the reform, and interact them with the $Reform_t$ dummy. We also account for pre-existing differences in the skill intensity of firms by including the share of skilled workers in 2004, interacted with the $Reform_t$ dummy, as an additional control.[6] We find that the growth in bank credit is 7.4 percentage points higher for firms in high-enforcement localities relative to firms in low-enforcement localities following the reform.

Moreover, the timing of this effect is entirely consistent with the reform. We provide evidence for this by estimating a version of Eq. (16) by quarter-year. This specification replaces the $Reform_t$ dummy with a dummy for each quarter-year, hence separately estimating the difference in bank credit growth for firms in high- and low-enforcement localities at each time period. The omitted period is the last quarter of 2004, which is the quarter prior to

[6] We measure economic development variables and skill intensity in 2004 and interact them with the $Reform_t$ dummy instead of including time-varying versions of these variables to avoid the issue of "bad controls." This issue is present in our setting because access to credit has been found to affect economic development and, as we show in the next section, skill intensity is also impacted by our credit shock.

the reform, so effects can be interpreted relative to this period. Panel A of Fig. 3 plots the coefficients of this regression model, along with 95% confidence intervals. We estimate a sizable and significant increase in bank credit growth for firms in high-enforcement localities relative to firms in low-enforcement localities starting in 2005. Importantly, our coefficient estimates are close to zero and statistically insignificant in the period preceding the reform. This implies that our estimated treatment effect is consistent with the timing of the reform at the quarterly level and, in particular, we find no evidence of pre-existing trends.[7]

In columns 3 and 4 of Table 4, we show that firms in high-enforcement localities also experience lower interest rate growth after the reform relative to firms in low-enforcement localities. In our preferred specification, the growth in interest rates is 1.7 percentage points lower for treated firms relative to control firms. This indicates that the reform led to higher quantities of credit and lower prices, which lends support to the theory that the reform caused an increase in the supply of credit.

Next, we investigate the response of firms' employment and investment decisions to the reform. Columns 5 and 6 of Table 4 show that firms in high-enforcement localities see higher overall employment growth following the reform. We find that firms in high-enforcement localities experience 1.3 percentage points higher employment growth after the reform, relative to firms in low-enforcement localities. Higher employment could be a consequence both of higher wages, which potentially make the firm more appealing to workers, or of firms' being better equipped to weather temporary shocks without laying off workers so as to economize on firing, hiring, and training costs. The latter, a phenomenon known as "labor hoarding," has been found to be negatively impacted by financial constraints (Giroud and Mueller, 2017). In column 8 of Table 4, our preferred specification, we show that investment, measured as total capital expenditures scaled by lagged total assets, grows by an additional

[7] Recall that credit registry data are available from 2003 onward at a quarterly frequency and data on employment outcomes are available from 2000 onward at an annual frequency. This explains the difference in the number of estimates between Panel A of Fig. 3 and the remaining panels.

6.9 percentage points for firms in high-enforcement localities following the reform relative to firms in low-enforcement localities.

These results are in line with firms experiencing a positive credit supply shock following the reform and suggest that firms increase their levels of investment and employment as a response to increased access to credit. Moreover, these firm-level results are consistent with previous municipality-level findings by Ponticelli and Alencar (2016), who also analyze the 2005 bankruptcy reform and find that average borrowing, employment, and investment is higher for firms in localities with less congested courts following the reform, relative to firms in localities with more-congested courts.

5.2 Effect on skill composition and on the skill premium

In this section, we present and discuss our key empirical findings. We show that firms in localities with less congested courts experience an increase in their skill intensity and their return to skill relative to firms in localities with more-congested courts, following the reform and the subsequent increase in access to bank credit. In Table 5, we present estimates of Eq. (16) for outcomes relating to the employment of skilled workers, with and without the inclusion of controls. This equation compares outcomes for firms in high-enforcement localities with those of firms in low-enforcement localities, before and after the reform. All models include firm fixed effects to account for any level differences between the two groups of firms; they also include state×time fixed effects to flexibly control for any time trends common to all firms in a given state. Standard errors are clustered at the locality level.

In column 1, we show an increase in the share of employees who are skilled, with workers considered skilled if they possess at least some post-secondary education and unskilled otherwise. In column 2 of Table 5, we include as controls local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. As before, these variables are measured in 2004, the year before the reform, and interacted with the $Reform_t$ dummy. We find that the growth in the share of skilled workers is 4.0 percentage points higher for firms in high-enforcement localities relative to firms in low-enforcement localities after the reform. While we show in subsequent sections that overall employment also rises as a consequence of increased borrowing capacity, this result speaks to the characteristics of the workers that a firm employs and to how these characteristics change when access to credit increases.

Columns 3 and 4 of Table 5 show a rise in the skill premium following the reform. For each year, we use a Mincer regression of log wages on gender, age, tenure, age squared, and tenure squared to back out composition-adjusted wages, and use those to construct the skill premium. We find that firms in high-enforcement localities experiencing 3.8 percentage points higher growth in the skill premium relative to firms in low-enforcement localities. This implies that increased access to credit affects not only the relative quantity of skilled labor but also its relative price, leading to a higher within-firm return to skill. This finding is consistent with subsequent work by Moser et al. (2020), who find that both between- and within-firm earnings inequality decline as a consequence of decreased access to credit.

Taken together, these findings suggest that access to credit allows firms to hire and retain relatively more skilled workers and that these firms do so by increasing their returns to skill. This is of particular importance given that the ability to hire and retain skilled labor has been shown to meaningfully impact firm-level productivity (Bloom et al., 2013; Bhattacharya et al., 2013).

Next, we investigate whether access to credit affects the composition of workers in terms of their occupations. To do so, we decompose employment into broad occupation groups and sort these groups according to the Acemoglu and Autor (2011) measure of intensity of use of nonroutine cognitive tasks. Intuitively, labor from workers who perform routine cognitive tasks is more easily replaceable by machinery and equipment (Autor et al., 2003). Conversely, we should expect that the demand for workers who perform nonroutine cognitive tasks does not decrease as much as firms invest more, and could even rise if capital and skilled labor are complements.

We show results of this exercise in Table 6, and our findings are entirely consistent with the capital-skill complementarity hypothesis. With or without controls, our point estimates are monotonically increasing in the intensity of use of nonroutine tasks, indicating that, following the reform, the relative demand for workers rises with the amount of nonroutine tasks that they perform. We find that treated firms increase their share of workers in managerial, professional, and technical occupations following the reform relative to firms in the control group. On the other hand, we estimate negative and statistically significant changes in the share of workers in production and operations and in service occupations, which are less intensive in nonroutine cognitive tasks.

Finally, in Panel B of Fig. 3, we show coefficient estimates and 95% confidence intervals for Eq. (18), which separately estimates the differences in the growth rate of the share of skilled workers for firms in high- and low-enforcement localities at each time period, by replacing the $Reform_t$ dummy with a dummy for each year. The omitted period in this specification is 2004, the year before the reform, so effects can be interpreted relative to this period.

We find that the timing of the effect is consistent with the reform. The estimates indicate that, for firms in high-enforcement localities, the growth in the share of skilled workers is 1.0, 4.3, 4.6, and 5.0 percentage points higher one, two, three, and four years after the reform, respectively. Importantly, our estimates are close to zero and statistically insignificant prior to the reform, showing no evidence of pre-existing trends. We show analogous results with the share of nonroutine workers—defined as workers in managerial, professional, and technical occupations—and with skill premium as outcome variables in Panels C and D of Fig. 3, respectively, and again find no evidence of pre-trends.

5.3 Analyzing the mechanism: capital-skill complementarity

In Section 5.1, we discuss how firms increase their levels of capital and employment as a response to increased access to credit. Along with the shift in the skill composition toward better-educated workers and toward workers who perform nonroutine cognitive tasks, shown in Section 5.2, these results are consistent with a production function featuring complementarities between capital and skilled labor. In this section, we provide direct evidence in support of the capital-skill complementarity hypothesis by showing that firms in high-enforcement regions in industries with high capital-skill complementary see a larger increase in the share of skilled workers and the skill premium following the bankruptcy reform, relative to firms in high-enforcement regions in industries with low capital-skill complementary. To do so, we use the parameter estimates obtained from the estimation procedure described in Section 3.2, which are available for all industries in manufacturing and extractive sectors, to compute the elasticity of substitution between capital and unskilled labor ($\varepsilon_{nk} = \frac{1}{1-\sigma}$) and between capital and skilled labor ($\varepsilon_{sk} = \frac{1}{1-\rho}$) for each 2-digit industry.

As we discuss in Section 3.2, we find that capital and skilled labor are relative complements in all manufacturing and extractive industries, meaning that our estimates imply that $\sigma > \rho$ (and hence $\varepsilon_{nk} > \varepsilon_{sk}$). To sort industries according to the degree of capital-skill complementarity, we use the ratio between the two elasticities of substitution ($\frac{\varepsilon_{nk}}{\varepsilon_{sk}}$) as a measure. Industries with high $\frac{\varepsilon_{nk}}{\varepsilon_{sk}}$ are such that the elasticity of substitution between unskilled labor and capital is much higher than the elasticity of substitution between skilled labor and capital, meaning that capital is much more complementary to skilled labor than to unskilled labor.

We sort firms into high and low complementarity according to this measure and estimate the following equation:

$$g(Y_{icjt}) = \beta_1 Reform_t \times HighEnforcement_c \times HighCSC_j + \beta_2 Reform_t \times HighCSC_j + \beta_3 X_{it} + \kappa_i + \theta_{ct} + \epsilon_{icjt}, \tag{19}$$

where $g(Y_{icjt})$ is the growth rate in the outcome of interest for firm i in locality c in industry j between the years $t-1$ and t; $Reform_t$ is a dummy that equals 0 prior to the reform and 1 after the reform; $HighEnforcement_c$ is a dummy for firm i being in a locality c with below-median court congestion; $HighCSC_j$ is a dummy for firm i being in an industry j above the median in our measure of capital-skill complementarity; X_{it} is a set of controls; κ_i is a vector of firm fixed effects; and θ_{ct} is a vector of locality-year fixed effects.

Note that, since we have industry-level variation in our measure of capital-skill complementarity, we can include locality-year fixed effects to control for unobserved time-varying differences between localities. This exercise should thus alleviate concerns that our results are driven by regional differences, in addition to shedding light on the mechanism through which increased access to credit impacts the skill composition of a firm's workforce.

We show estimation results for Eq. (19) in Table 7, with and without controls.[8] According to our preferred specification, firms in high-complementarity industries and high-enforcement localities see 5.1 and 4.9 percentage points higher growth in the share of skilled workers and the skill premium, respectively, following the bankruptcy reform, relative to firms in low-complementarity industries and high-enforcement localities. These results suggest that firms in high-complementarity industries increase their utilization of skilled labor and their return to skill by more than firms in low-complementarity industries as a response to increased access to credit. These findings thus lend support to the theory that capital-skill complementarity is the mechanism behind the effect of a relaxation of credit constraints on the skill composition and the skill premium in our setting.[9]

[8] For completeness, we also show estimation results for Eq. (19) with credit and investment as dependent variables in Appendix Table B1.

[9] These findings supporting the importance of capital-skill complementarity as a mechanism are consistent

To assess the robustness of these results, we report estimates obtained using two alternative measures of capital-skill complementarity. The first is the index of Larrain (2015), constructed by estimating skilled-labor-share equations for both manufacturing and non-manufacturing industries using data from 20 mainly European countries from 1975 to 2005. We sort firms into high and low complementarity along the median according to this measure, which is reported in Table 4, Column 4 of Larrain (2015). As in the current study, Larrain (2015) finds that all manufacturing sectors exhibit some degree of capital-skill complementarity. This work also finds that manufacturing industries are among the highest-complementarity sectors, as unskilled workers in manufacturing tend to perform more routine tasks. Our second alternative measure of capital skill complementarity builds on this finding and splits firms into manufacturing and non-manufacturing sectors as a measure of high and low capital-skill complementarity.

We report results of this estimation in Appendix Table B2. According to both alternative measures, we find that firms in high-complementarity industries increase their skill intensity and their skill premium by more than firms in low-complementarity industries following a relaxation of credit constraints. This is further evidence in favor of the capital-skill complementarity mechanism and should alleviate concerns that the results presented in this section are somehow driven by our production function estimation procedure.

Finally, in Fig. B1, we show coefficient estimates and 95% confidence intervals for a dynamic version of Eq. (19), replacing the $Reform_t$ dummy with a dummy for each year. The omitted period in this specification is 2004, the year before the reform, so effects can be interpreted relative to this period. We find that the timing of the effect by degree of capital-skill complementarity is consistent with the reform and find no evidence of pre-trends.

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with the evidence in Bau and Matray (2020), who find that capital account liberalization in India led to higher investment and higher wage bills for capital-constrained firms, relative to unconstrained firms.

5.4 Reallocation of skill to financially constrained firms

The model of Section 3 suggests that financially constrained firms should experience larger employment and investment effects as a consequence of the 2005 reform and the subsequent increase in access to credit. In this section, we take this prediction to the data by exploiting heterogeneity in how financially constrained firms were prior to the reform.

Hadlock and Pierce (2010) assess the informativeness of several measures of financial frictions and find that size and age are the most successful predictors of financial constraints. Specifically, financially constrained firms are, on average, smaller and younger than unconstrained firms. Based on these finding, we estimate the following specification:

$$\begin{aligned} g(Y_{ict}) = &\beta_1 Reform_t \times HighEnforcement_c \times Constrained_i + \\ &\beta_2 Reform_t \times Constrained_i + \beta_3 X_{it} + \kappa_i + \theta_{ct} + \epsilon_{ict}, \end{aligned} \tag{20}$$

where $g(Y_{ict})$ is the growth rate in the outcome of interest for firm i in locality c between the years $t-1$ and t; $Reform_t$ is a dummy that equals 0 before the reform and 1 after the reform, $HighEnforcement_c$ is a dummy for firm i being in a locality c with below-median court congestion; $Constrained_i$ is either a dummy for a firm being below the median in firm size (measured by the number of employees) in the years preceding the reform or a dummy for a firm being below the median in firm age in the years preceding the reform; X_{it} is a set of controls; κ_i is a vector of firm fixed effects; θ_{ct} is a vector of locality-year fixed effects.

As in the previous section, since we have firm-level variation in the degree of financial constraints prior to the reform, we can include locality-time fixed effects in this specification and control for unobserved time-varying differences between localities. Thus, in addition to testing the hypothesis that financially constrained firms were disproportionately affected by the reform, this exercise serves to alleviate concerns that our results are driven by unobserved time-varying regional differences.

We report results of this exercise in Table 8.[10] In both sets of results, we find that the share of skilled workers (measured by educational attainment in columns 1 and 2 and by occupation in columns 3 and 4) increases for financially constrained firms in high-enforcement localities relative to unconstrained firms in high-enforcement localities. We also find that the skill premium rises for financially constrained firms in high-enforcement localities relative to unconstrained firms in high-enforcement localities.

Next, we leverage the fact that we can follow an individual worker's career path to show direct evidence that skilled labor is reallocated from financially unconstrained firms to financially constrained firms following the reform. To do so, we decompose the total share of skilled workers at a given firm into the share of skilled workers who worked at an unconstrained firm prior to the reform and the share of workers without a pre-reform employment spell at an unconstrained firm. We further split the share of workers without a pre-reform employment spell at an unconstrained firm into (1) workers with a previous employment spell at a constrained firm; and (2) workers that appear in our matched employer-employee data for the first time, which we refer to as new entrants. In line with the previous analysis, we call a firm unconstrained if it is not categorized as constrained according to our size and age definitions.

We show results of this exercise in Table 9. Our findings suggest that the rise in the share of skilled workers at constrained treated firms, relative to unconstrained treated firms, is entirely driven by a reallocation of skilled labor from unconstrained firms to constrained firms. In particular, we find a sizable and statistically significant increase in the share of skilled workers with a previous employment spell at an unconstrained firm. Conversely, our estimates for the share of skilled workers without a previous employment spell at an unconstrained firm are small and statistically insignificant, both for new entrants and for

[10] For completeness, we also show estimation results for Eq. (20) with credit and investment as dependent variables in Appendix Table B3

workers with a previous spell at a constrained firm. This suggests that the shift in skill composition comes from the fact that constrained firms are better equipped to poach skilled workers from their unconstrained competitors when financial constraints are loosened.

We also estimate dynamic versions of Eq. (20) with size and age as proxies of financial constrains and report coefficient estimates and 95% confidence intervals in Appendix Figs. B2 and B3, respectively. As before, the timing of results is consistent with the reform and we find no evidence of pre-existing trends.

Taken together these results indicate that increased access to bank credit following the reform impacted not only the overall level of skill utilization but also the allocation of skill, with financially constrained increasing their employment of skilled workers relative to unconstrained firms. This is evidence that financial development, in the form of increased access to bank credit, can impact the allocation not only of capital, but also of skill. This is important given the evidence that misallocation of resources is an important source of productivity differences between high- and low-income countries (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009).

5.5 Controlling for industry-specific trends

One potential challenge to our identification strategy is that industry shares in high- and low-enforcement localities might systematically differ, and that sectors based in high-enforcement localities might experience differential growth from 2005 onward. This would be problematic as it would be consistent with the lack of pre-existing trends shown in Section 5, but would imply that something other than access to credit is the driving force behind our results.

To alleviate these concerns, we assess the robustness of our results to flexibly controlling for industry–specific trends through the inclusion of fixed effects. In Appendix Table B4, we show that our results are robust to including 2-digit-industry×time fixed effects to the specification in Eq. (16), with or without the inclusion of controls. This specification compares outcomes for firms in high- and low-enforcement localities that are in the same 2-digit industry, before and after the reform. Estimates from this specification are qualitatively identical to our baseline results, thus providing strong evidence against the possibility that our results are driven by industry-specific trends.

5.6 Controlling for funding needs

In Section 5.4, we show that financially constrained firms increase their skill intensity and their returns to skill relative to unconstrained firms. This raises the potential concern that our results are driven by differences in funding needs across treatment and control groups.

We address this concern by adding firm size (measured by average log total employment in 2004, the year before the reform, interacted with the $Reform_t$ dummy) and firm age, which are good proxies for financial constraints (Hadlock and Pierce, 2010), as controls in Eq. (16).[11] We report estimates from this specification in Appendix Table B5 and find that our results are robust to controlling for firm-level proxies of funding needs. The fact that our results are robust to controlling for firm age is also reassuring in light of evidence that the pay structure at young and old firms is systematically impacted by worker selection (Babina et al., 2019).

6 Conclusion

In this paper, we investigate the effect of increased access to bank credit on the employment and earnings of high- and low-skilled workers. Our comprehensive data set provides information not only on bank lending, investment, employment, and wages but also on char-

[11] We include log employment in 2004 interacted with the $Reform_t$ dummy as a control instead of log employment because employment itself is affected by our credit shock and is thus a "bad control."

acteristics of workers, such as education and occupation. Our identification strategy exploits a considerable reform to bankruptcy legislation undertaken by Brazil in 2005 that strengthened creditor rights. This reform led to an increase in the borrowing capacity of firms in regions with less congested civil courts, which were better positioned to enforce the new legislation. We show that the credit expansion resulting from the reform led to an increase in firms' skill intensity and skill premium, and to a reallocation of skilled labor from financially unconstrained firms to constrained firms. We also find that the effect of credit on skill intensity is stronger in industries with a high degree of capital-skill complementarity.

Our results indicate that increased access to bank credit impacts not only investment and total employment but also the type of worker a firm employs, in terms of both educational attainment and occupation. We establish a credible causal link between access to credit and a firm's utilization of skilled labor, providing new evidence on the specific channels through which financial development can impact the allocation of production factors. We also provide direct evidence that a relative complementarity between capital and skilled labor is a key mechanism through which access to credit impacts the relative utilization of skill and the returns to skill in our setting.

We view the importance of these results through the lens of evidence that misallocation of resources is a key source of productivity differences across high- and low-income countries (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Taken together, these findings suggest that policies such as the 2005 bankruptcy reform can increase the aggregate productivity of developing countries by broadening access to bank credit and, consequently, improving the allocation of production factors.

In addition, we show that increased access to bank credit increases within-firm earnings inequality by increasing the return to skill. This suggests that skilled workers emerge as the relative winners in this context and highlights the potential distributional consequences of policies such as the 2005 bankruptcy reform.

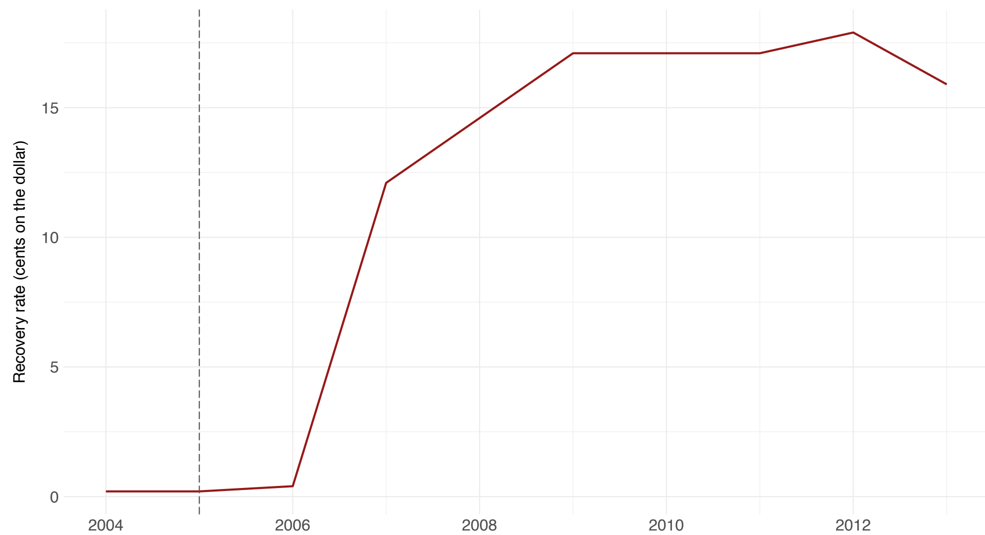
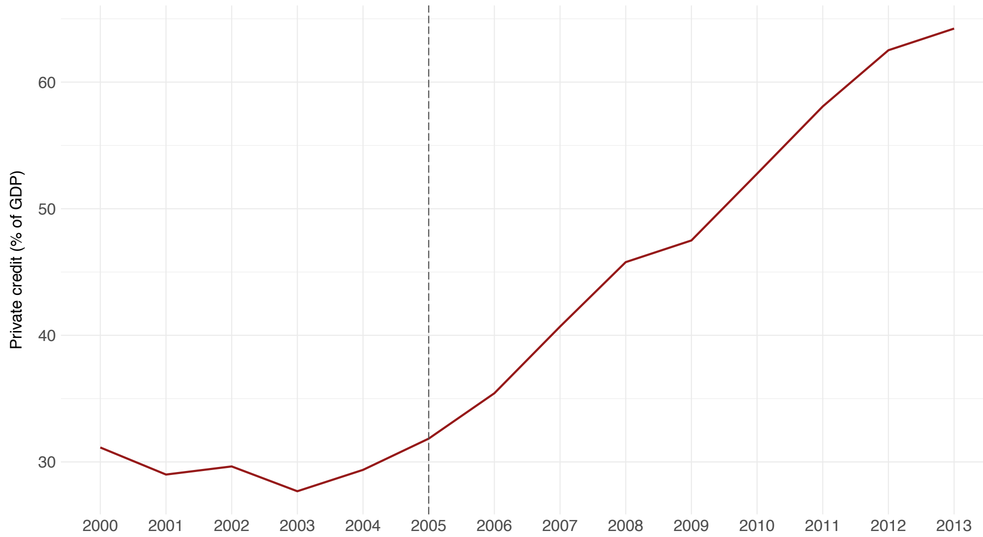
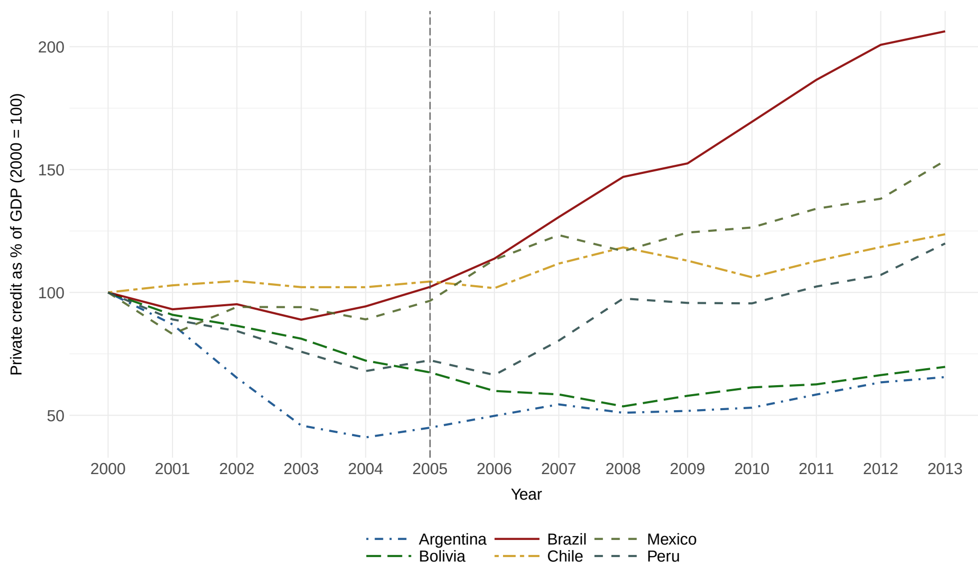


Figure 1: Expected recovery rate of secured creditors (cents on the dollar)

This figure shows the expected recovery rate for secured creditors in Brazil. Data comes from World Bank's Doing Business database.



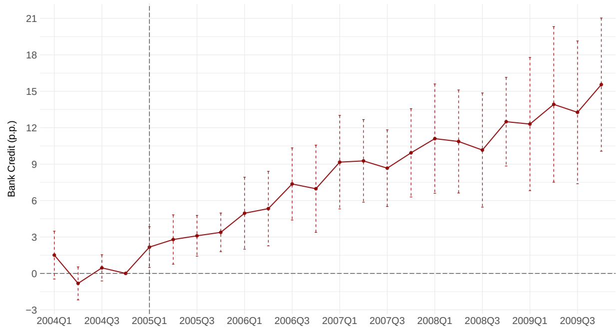
(a) Brazil



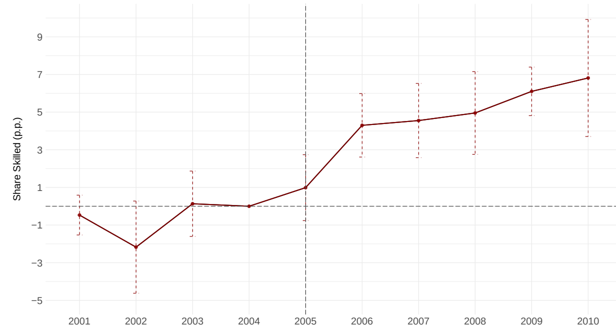
(b) Comparison with Latin America

Figure 2: Private Credit as Percentage of GDP (%)

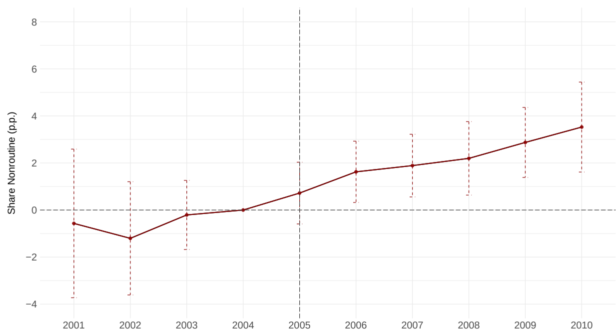
This figure shows private credit as percentage of GDP. In panel A, we plot private credit as percentage of GDP in Brazil. In panel B, we superimpose the evolution of private credit for a subsample of other Latin-American countries. Data on private credit comes from the IMF.



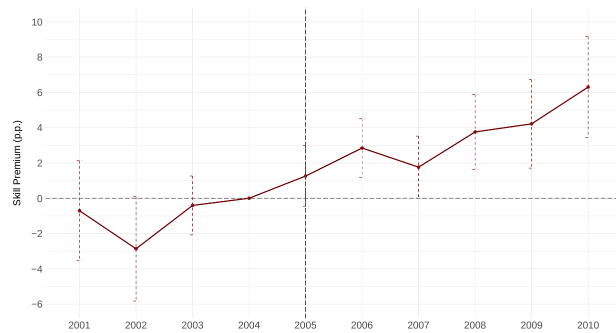
(a) Bank Credit



(b) Share Skilled



(c) Share Nonroutine



(d) Skill Premium

Figure 3: Timing of Effect on Bank Credit, on Skill Intensity and on the Skill Premium

This figure shows the timing of the effect of the 2005 bankruptcy reform on bank credit (panel A), on the share of skilled workers (panel B), on the share of workers in managerial, professional, and technical occupations (panel C), and on the skill premium (panel D). We plot coefficient estimates from Eq. (18) along with 95% confidence intervals, with dependent variables in growth rates. Bank Credit is the sum of all outstanding bank loans for a given firm in a given quarter-year. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Observation is at the firm-quarter-year level in Panel A and at the firm-year level in the remaining panels. Standard errors are clustered at the AMC level. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Credit registry data is available from 2003 onward at a quarterly frequency and employment outcomes are available from 2000 onward at an annual frequency.

Table 1: Summary Statistics

Panel A: Firm characteristics

	Mean	Med.	St. Dev.	N
Total bank debt	216.74	40.84	4,410.01	2,907,501
Number of loans	9.82	6.00	10.29	2,907,501
Interest rate	25.94	20.07	20.33	2,147,499
Firm age	14.00	12.08	8.05	2,373,611
Number of workers	39.49	11.00	97.70	2,373,611
Share skilled	0.21	0.14	0.21	2,373,611
Share nonroutine	0.22	0.12	0.27	2,373,611
Average monthly wages	0.87	0.70	0.73	2,373,611
Average skill premium	1.55	1.21	1.79	2,373,611
Investment/assets	0.05	0.02	0.09	227,920
Assets	12,009.94	2,169.54	22,054.36	227,920
Output	14,351.56	3,709.67	23,697.11	227,920
Capital/output	0.64	0.55	0.57	227,920
Value added per worker	71.12	37.88	209.18	227,920

Panel B: Locality characteristics

	Mean	Med.	St. Dev.	N
Local GDP per capita	8.61	6.83	9.00	2,876
Bank branches per 100,000 people	14.09	11.71	9.60	2,876
Manufacturing share in local value added	21.05	14.80	16.24	2,876

Notes: This table shows descriptive statistics for firms in our sample, with credit registry data at the firm-quarter-year level, and data on employment outcomes and real outcomes at the firm-year level. We restrict our attention to private firms present in our sample prior to the 2005 bankruptcy reform. We obtain employment outcomes from the RAIS dataset from 2000 onward at an annual frequency. Real outcomes come from the PIA dataset and are available from 2000 onward at an annual frequency. The PIA dataset has information on firms in manufacturing and extractive sectors with at least 30 employees. We obtain credit outcomes from the SCR dataset, available from 2003 onward at a quarterly frequency. This dataset has information on firms with loans totaling at least 5,000 BRL. We obtain locality characteristics in 2004 from the Brazilian Institute of Geography and Statistics (IBGE). Monetary values are in thousands of 2003 BRL.

Table 2: Parameters

Sector	Code	σ	ρ	ν	τ
Coal mining	10	0.45	0.02	0.38	0.71
Oil and gas extraction	11	0.83	-0.33	0.10	0.91
Metallic mineral mining	13	0.53	-0.31	0.23	0.85
Non-metallic mineral mining	14	0.54	-0.07	0.32	0.67
Food products	15	0.52	-0.15	0.26	0.77
Tobacco products	16	0.56	-0.25	0.27	0.80
Textile products	17	0.72	-0.32	0.08	0.81
Apparel and other products	18	0.26	-0.31	0.10	0.94
Leather and leather products	19	0.80	-0.30	0.25	0.79
Wood products	20	-0.10	-0.19	0.36	0.88
Paper products	21	0.55	-0.10	0.40	0.76
Editing, printing, and publishing	22	0.96	-0.38	0.07	0.92
Coke production	23	0.55	-0.28	0.34	0.80
Chemicals	24	0.98	-0.39	0.05	0.96
Rubber and plastics	25	0.50	-0.16	0.25	0.86
Non-metallic mineral products	26	0.85	-0.34	0.09	0.81
Primary metal	27	0.55	-0.33	0.07	0.91
Metal products	28	0.68	-0.07	0.08	0.52
Machinery and equipment	29	0.37	0.04	0.41	0.61
Office equipment	30	0.56	-0.20	0.10	0.78
Electronic equipment	31	0.84	-0.36	0.08	0.90
Telecommunication equipment	32	0.90	-0.37	0.06	0.90
Medical equipment	33	0.51	-0.32	0.22	0.90
Automotive vehicles	34	0.90	-0.36	0.09	0.90
Other transportation equipment	35	0.58	-0.43	0.05	0.96
Furniture and miscellaneous industries	36	0.62	-0.32	0.10	0.81
Recycling	37	0.49	-0.05	0.09	0.77

Notes: This table reports results from the two-step estimation of production function parameters for each 2-digit industry described in Section 3.2 using data from our PIA-RAIS sample from 2000 to 2010. Code is the 2-digit CNAE 1.0 industry code for each sector.

Table 3: Comparing Treatment and Control

Panel A: Comparing firms in treated and control localities

	High - Low enforcement	P-value
Log number of workers	-0.024	0.16
Firm age	-0.000	0.67
Share skilled	0.008	0.00***
Share nonroutine	0.003	0.17
Skill premium	-0.017	0.41
Investment/assets	-0.001	0.78
Log bank credit	0.009	0.52

Panel B: Comparing treated and control localities

	High - Low enforcement	P-value
Local GDP per capita	0.042	0.90
Bank branches per 100,000 people	-0.631	0.18
Manufacturing share in local value added	-0.257	0.97

Notes: This table compares characteristics of the treatment and control groups in the pre-reform period. In Panel A, we report differences in firm characteristics between high-enforcement (treated) and low-enforcement (control) localities, along with p values. The differences reported in Panel A control for firm and state-year fixed effects, and standard errors are clustered at the AMC level. In Panel B, we report differences between high-enforcement (treated) and low-enforcement (control) localities in characteristics at the locality level in 2004, along with p values. The differences reported in Panel B control for state fixed effects and standard errors are clustered at the AMC level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of Bankruptcy Reform on Credit, Employment, and Investment

Dependent Variable:	Bank Credit		Interest Rate		Employment		Investment/Assets	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reform×HighEnforcement	**0.078*****	**0.074*****	**-0.015***	**-0.017****	**0.009*****	**0.013*****	**0.072*****	**0.069*****
	(0.011)	(0.010)	(0.009)	(0.007)	(0.003)	(0.002)	(0.012)	(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with the dependent variables in growth rates. Bank Credit is the sum of all outstanding bank loans for a given firm. Interest Rate is the average interest rate across all outstanding bank loans for a given firm. Employment is the total number of employees. Investment/Assets is total capital expenditures divided by lagged assets. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Regressions in columns 1 to 4 include 2,907,501 firm-quarter-year observations. Employment regressions include 2,373,611 firm-year observations and Investment regressions include 227,920 firm-year observations. Credit registry data is available from 2003 onward at a quarterly frequency and employment and investment outcomes are available from 2000 onward at an annual frequency. Investment information is only available for firms in extractive and manufacturing sectors with at least 30 employees. These differences in sample and frequency explain the differences in the number of observations across regressions. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Bankruptcy Reform on Skill Composition and Skill Premium

Dependent Variable:	Share Skilled		Skill Premium	
	(1)	(2)	(3)	(4)
Reform×HighEnforcement	**0.044*****	**0.040*****	**0.046*****	**0.038*****
	(0.008)	(0.008)	(0.008)	(0.007)
Firm FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of Bankruptcy Reform by Nonroutine Task Intensity

	Intensity of use of nonroutine tasks ←							
Dependent Variable:	Managerial, Professional, Technical		Clerical, Sales		Production, Operators		Service	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reform×HighEnforcement	**0.029*****	**0.022****	**0.005**	**0.001**	**-0.031****	**-0.023****	**-0.049****	**-0.030***
	(0.007)	(0.008)	(0.005)	(0.004)	(0.015)	(0.012)	(0.024)	(0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with all dependent variables in growth rates. Managerial, Professional, Technical is the ratio of employees in managerial, professional, and technical occupations to total employment. Clerical, Sales is the ratio of clerical and sales workers to total employment. Production, Operators is the share of production and operation workers to total employment. Service is the share of service workers to total employment. Standard errors, clustered at the AMC level, are reported in parentheses. Intensity of use of nonroutine tasks is given by the Acemoglu and Autor (2011) measure of nonroutine cognitive task intensity. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Results by Degree of Capital-Skill Complementarity

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement×HighCSC	**0.039****	**0.051*****	**0.048*****	**0.045****	**0.044****	**0.049*****
	(0.017)	(0.017)	(0.015)	(0.014)	(0.017)	(0.017)
Reform×HighCSC	0.000	-0.012	-0.021	-0.019	-0.002	0.002
	(0.013)	(0.040)	(0.011)	(0.030)	(0.012)	(0.039)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (19), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. High CSC is a dummy for a firm being in an industry that is above the median in our measure of capital-skill complementarity. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 519,554 firm-year observations. The number of observations differs from previous regressions of employment outcomes because our baseline measure of capital-skill complementarity is only available for industries in manufacturing and extractive sectors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Results by Degree of Financial Constraints

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement×Small	**0.031*****		**0.032*****		**0.023*****	
	(0.009)		(0.009)		(0.009)	
Reform×HighEnforcement×Young		**0.021****		**0.028****		**0.017****
		(0.010)		(0.010)		(0.008)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (20), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Small is a dummy for a firm being smaller than the median firm, with size measured as number of employees. Young is a dummy for a firm being younger than the median firm. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Reallocation of Skill from Unconstrained to Constrained Firms

Dependent Variable:	Share Skilled							
	Total		From Unconstrained		Not From Unconstrained			
					From Constrained		New Entrants	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reform×HighEnforcement×Small	**0.031*****		**0.062*****		**0.004**		**0.015**	
	(0.009)		(0.015)		(0.003)		(0.028)	
Reform×HighEnforcement×Young		**0.021****		**0.047****		**-0.013**		**0.007**
		(0.010)		(0.020)		(0.021)		(0.035)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (20), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Total refers to the share of all skilled workers, regardless of previous employment history. From Unconstrained is the share of skilled workers with a pre-reform employment spell at an unconstrained firm (defined as being larger than the median firm and older than the median firm). Not From Unconstrained is the share of skilled workers without a pre-reform employment spell at an unconstrained firm. From Constrained is the share of skilled workers without a pre-reform employment spell at an unconstrained firm, but with a spell at a constrained firm. New Entrants the share of skilled workers without a pre-reform employment spell at any firm, constrained or unconstrained. Small is a dummy for a firm being smaller than the median firm, with size measured as number of employees. Young is a dummy for a firm being younger than the median firm. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A Production function estimation

Our production function estimation procedure closely follows De Loecker and Warzynski (2012). Consider the following production function

$$q_{it} = f(s_{it}, n_{it}, k_{it}; \gamma) + \omega_{it} + \varepsilon_{it} \tag{21}$$

where q_{it} is logged value added, s_{it} is logged skilled labor, n_{it} is logged unskilled labor, k_{it} is logged capital, γ collects all coefficients, and ω_{it} is logged physical productivity (TFPQ). Our baseline specification relies on a translog functional form for $f()$, which is equivalent to approximating $f()$ by a second-order polynomial in which all inputs, inputs squared, and interaction terms between all inputs are included (in log form). We consider a translog production function of the form

$$q_{it} = \gamma_s s_{it} + \gamma_n n_{it} + \gamma_k k_{it} + \sum_{x \in \{s,n,k\}} \gamma_{xx} x_i^2 + \sum_{w \neq x} \sum_{x \in \{s,n,k\}} \gamma_{xw} x_{it} w_{it} + \omega_{it} + \varepsilon_{it} \tag{22}$$

In order to consistently estimate production function coefficients, we need to control for unobserved productivity shocks, since those are potentially correlated with input choices. We deal with this issue by relying on proxy methods developed by Olley and Pakes (1996) and Levinsohn and Petrin (2003), use material demand

$$m_{it} = m_t(k_{it}, \omega_{it}, s_{it}, n_{it}) \tag{23}$$

to proxy for productivity by inverting $m_t()$. We hence assume that the demand for materials is strictly monotone in ω_{it}.

We follow Ackerberg et al. (2015) and estimate all relevant coefficients using second-stage moments, instead of attempting to identify labor coefficients in the first stage as in Levinsohn and Petrin (2003).[12] In the first stage, we estimate

$$q_{it} = \phi(s_{it}, n_{it}, k_{it}, m_{it}) + \varepsilon_{it} \tag{24}$$

and obtain an estimate of expected output ($\hat{\phi}$) and an estimate of ε_{it}. In the second stage, we rely on the assumed law of motion for productivity

$$\omega_{it} = g_t(\omega_{it}) + \xi_{it} \tag{25}$$

For a given set of parameters γ, we can compute $\omega_{it}(\gamma) = \hat{\phi} - \gamma_s s_{it} - \gamma_n n_{it} - \gamma_k k_{it} - \sum_{x\in\{s,n,k\}} \gamma_{xx} x_{it} - \sum_{z\neq x} \sum_{x\in\{s,n,k\}} x_{it} w_{it}$. We can then regress $\omega_{it}(\gamma)$ on its lag and recover the innovation to productivity (conditional on the set of parameters γ) $\xi_{it}(\gamma)$. We then estimate the production function parameters using GMM and moment conditions of the form

$$\mathbb{E}[\xi_{it}(\gamma) z^j] = 0 \; j \in \{s, n, k\}$$
$$\mathbb{E}[\xi_{it}(\gamma) z^j z^h] = 0 \; j, h \in \{s, n, k\}$$

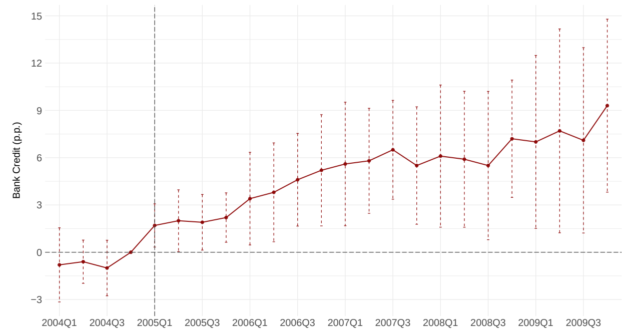
where z^j, $j \in \{s, n, k\}$, is an instrument for skilled labor, unskilled labor, capital, or materials. We assume capital is decided one period ahead and is thus not correlated with the innovation in productivity. Under that assumption, we can use capital as its own instrument. We use lagged skilled and unskilled labor as instruments for skilled and unskilled labor, respectively. In order for these instruments to be valid, we require that skilled and unskilled

[12] See Ackerberg et al. (2015) and Wooldridge (2009) for a discussion of the issues with this approach.

wages be correlated over time, an assumption that is supported by our data.

We measure value added as the difference between deflated net revenue and deflated intermediate inputs, and measure materials as the deflated value of intermediate inputs. We measure skilled labor as the number of workers with at least some college education and unskilled labor as the number of workers with no college education. Finally, we measure capital as the deflated book value of fixed assets.

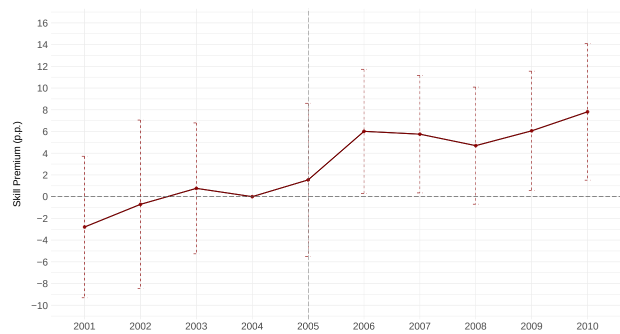
Appendix B Additional results



(a) Bank Credit

(b) Share Skilled

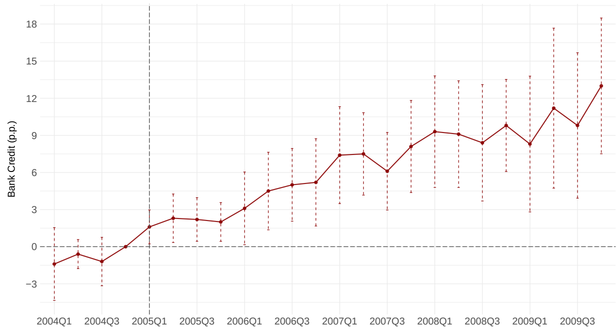
(c) Share Nonroutine



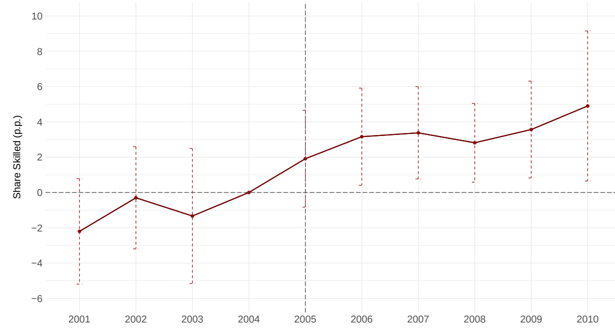
(d) Skill Premium

Appendix Figure B1: Timing of Effect by Degree of Capital-Skill Complementarity

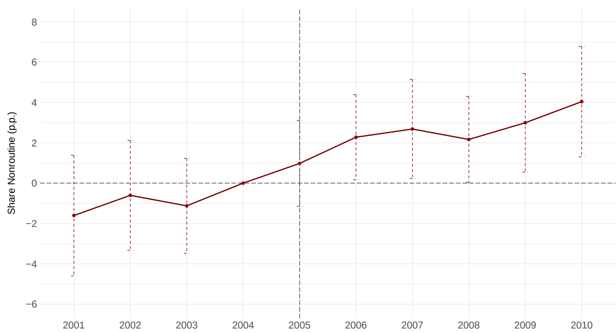
This figure shows the timing of the effect of the 2005 bankruptcy reform on bank credit (panel A), on the share of skilled workers (panel B), on the share of workers in managerial, professional, and technical occupations (panel C), and on the skill premium (panel D). We plot coefficient estimates and 95% confidence intervals from a dynamic version of Eq. (19), in which we replace the $Reform_t$ dummy with a dummy for each time period, with dependent variables in growth rates. Bank Credit is the sum of all outstanding bank loans for a given firm in a given quarter-year. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Observation is at the firm-quarter-year level in Panel A and at the firm-year level in the remaining panels. Standard errors are clustered at the AMC level. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Credit registry data is available from 2003 onward at a quarterly frequency and employment outcomes are available from 2000 onward at an annual frequency.



(a) Bank Credit



(b) Share Skilled

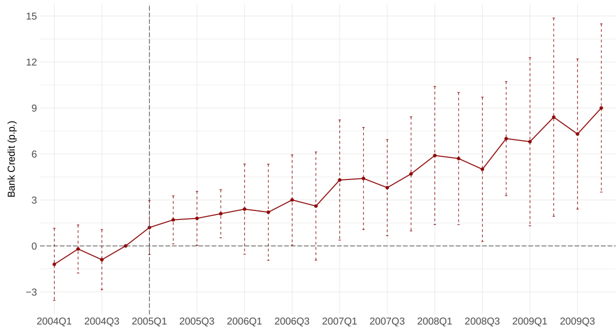


(c) Share Nonroutine

(d) Skill Premium

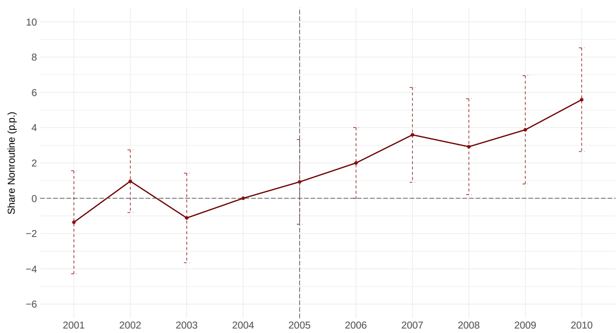
Appendix Figure B2: Timing of Effect by Firm Size

This figure shows the timing of the effect of the 2005 bankruptcy reform on bank credit (panel A), on the share of skilled workers (panel B), on the share of workers in managerial, professional, and technical occupations (panel C), and on the skill premium (panel D). We plot coefficient estimates and 95% confidence intervals from a dynamic version of Eq. (20), in which we replace the $Reform_t$ dummy with a dummy for each time period, with dependent variables in growth rates and $Constrained_i$ given by a dummy for a firm being smaller than the median firm. Bank Credit is the sum of all outstanding bank loans for a given firm in a given quarter-year. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Observation is at the firm-quarter-year level in Panel A and at the firm-year level in the remaining panels. Standard errors are clustered at the AMC level. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Credit registry data is available from 2003 onward at a quarterly frequency and employment outcomes are available from 2000 onward at an annual frequency.



(a) Bank Credit

(b) Share Skilled



(c) Share Nonroutine

(d) Skill Premium

Appendix Figure B3: Timing of Effect by Firm Age

This figure shows the timing of the effect of the 2005 bankruptcy reform on bank credit (panel A), on the share of skilled workers (panel B), on the share of workers in managerial, professional, and technical occupations (panel C), and on the skill premium (panel D). We plot coefficient estimates and 95% confidence intervals from a dynamic version of Eq. (20), in which we replace the $Reform_t$ dummy with a dummy for each time period, with dependent variables in growth rates and $Constrained_i$ given by a dummy for a firm being younger than the median firm. Bank Credit is the sum of all outstanding bank loans for a given firm in a given quarter-year. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Observation is at the firm-quarter-year level in Panel A and at the firm-year level in the remaining panels. Standard errors are clustered at the AMC level. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Credit registry data is available from 2003 onward at a quarterly frequency and employment outcomes are available from 2000 onward at an annual frequency.

Appendix Table B1: Effect on Credit And Investment by Degree of Capital-Skill Complementarity

Dependent Variable:	Bank Credit		Investment/Assets	
	(1)	(2)	(3)	(4)
Reform×HighEnforcement×HighCSC	**0.058****	**0.053*****	**0.041*****	**0.038*****
	(0.017)	(0.016)	(0.017)	(0.015)
Reform×HighCSC	0.001	0.010	-0.012	0.015
	(0.015)	(0.020)	(0.019)	(0.025)
Firm FE	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with all dependent variables in growth rates. Bank Credit is the sum of all outstanding bank loans for a given firm. Investment/Assets is total capital expenditures divided by lagged assets. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. The regressions in columns 1 and 2 include 2,907,501 firm-quarter-year observations and the regressions in columns 3 and 4 include 227,920 firm-year observations. The number of observations differs across regressions because real outcomes such as investment are only available for firms in extractive and manufacturing sectors with at least 30 employees and at a yearly frequency. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B2: Robustness to Different Measures of Capital-Skill Complementarity

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement×HighCSC$_1$	**0.055*****		**0.027****		**0.058*****	
	(0.011)		(0.010)		(0.010)	
Reform×HighEnforcement×HighCSC$_2$		**0.041****		**0.018**		**0.036****
		(0.015)		(0.011)		(0.014)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (19), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. High CSC$_1$ is a dummy for a firm being in an industry that is above the median according to the capital-skill complementarity measure in Larrain (2015). High CSC$_2$ is a dummy for a firm being in an industry in the manufacturing sector. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Regressions in odd-numbered columns include 1,670,813 firm-year observations and regressions in even-numbered columns include 2,373,611 firm-year observations. The difference in the number of observations is due to the fact that the Larrain (2015) measure of capital-skill complementarity is not available for all sectors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B3: Effect on Credit And Investment by Degree of Financial Constraints

Dependent Variable:	Bank Credit		Investment/Assets	
	(1)	(2)	(3)	(4)
Reform×HighEnforcement×Small	**0.062*****		**0.041****	
	(0.019)		(0.015)	
Reform×HighEnforcement×Young		**0.039****		**0.032****
		(0.015)		(0.013)
Firm FE	Yes	Yes	Yes	Yes
AMC-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (20), with all dependent variables in growth rates. Bank Credit is the sum of all outstanding bank loans for a given firm. Investment/Assets is total capital expenditures divided by lagged assets. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. The regressions in columns 1 and 2 include 2,907,501 firm-quarter-year observations and the regressions in columns 3 and 4 include 227,920 firm-year observations. The number of observations differs across regressions because real outcomes such as investment are only available for firms in extractive and manufacturing sectors with at least 30 employees and at a yearly frequency. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B4: Robustness to Controlling for Industry-Specific Trends

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement	**0.030*****	**0.028*****	**0.026*****	**0.022*****	**0.031*****	**0.027*****
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16) including 2-digit-industry×time fixed effects, with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Industry refers to 2-digit industry fixed effects. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B5: Robustness to Controlling for Funding Needs

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement	**0.040*****	**0.025*****	**0.022****	**0.015**	**0.039*****	**0.021*****
	(0.008)	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Funding Need Controls	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with all dependent variables in growth rates. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Baseline controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Baseline control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Funding need controls include log employment (measured in 2004 and interacted with the $Reform_t$ dummy) and firm age. Each regression includes 2,373,611 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table B6: Robustness to Using Logs instead of Growth Rates

Dependent Variable:	Share Skilled		Share Nonroutine		Skill Premium	
	(1)	(2)	(3)	(4)	(5)	(6)
Reform×HighEnforcement	**0.021*****	**0.020*****	**0.018*****	**0.023*****	**0.009*****	**0.011*****
	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)	(0.004)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Notes: All columns report estimates of the linear regression model specified in Eq. (16), with all dependent variables in logs. Share Skilled is the ratio of skilled workers to total employment, with a worker being categorized as skilled if possessing at least some post-secondary education. Share Nonroutine is the ratio of managers, professionals, and technicians to total employment. Skill Premium is the ratio of average hourly wages of high- and low-skilled workers. We adjust wages for composition using Mincer regressions of log wages on gender, age, tenure, age squared, and tenure squared. Standard errors, clustered at the AMC level, are reported in parentheses. The bottom rows specify the fixed effects and controls included in each column. Controls include local GDP per capita, the share of manufacturing in local value added, the number of bank branches per 100,000 people, and the firm-level share of skilled workers. Control variables are measured in 2004, the year prior to the reform, and interacted with the $Reform_t$ dummy. Each regression includes 2,044,035 firm-year observations. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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