Credit Supply, Firms, and Earnings Inequality*

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June 29, 2020

Abstract

We study the distributional effects of a monetary policy-induced firm-level credit supply shock on individual wages and employment. To this end, we construct a novel dataset that links worker employment histories to firms' bank credit relationships in Germany. We document that firms in relationships with banks that were more exposed to the introduction of negative monetary policy rates in 2014 experience a relative reduction in credit supply. A negative credit supply shock in turn is associated with lower firm-level average wages and employment. These effects are concentrated among distinct worker groups within firms. Initially lower-paid workers are more likely to be fired, while initially higher-paid workers see relative wage declines. At the same time, wages fall by more at initially higher-paying firms. Consequently, wage inequality within and between firms decreases. Our results suggest that firm credit has important distributional consequences in the labor market.

Keywords: Credit Supply, Passthrough, Employment, Wages, Earnings Inequality, Worker and Firm Heterogeneity, Linked Employer-Employee Data, Bank Relationships, Monetary Policy, Negative Interest Rates

JEL Classification: J31, E24, J23, G21, E51

*We thank our discussants Maarten De Ridder, Jack Favilukis, Hyunseob Kim, and Thomas Lambert. We also thank Niklas Amberg, Olivier Darmouni, Andrés Drenik, Alexandra Effenberger, Simon Jäger, Kyle Herkenhoff, Kilian Huber, Matthias Kehrig, Leo Kaas, Rick Mishkin, Paige Ouimet, Tommaso Porzio, Sergio Salgado, Fabiano Schivardi, Jesse Schreger, Petr Sedlacek, Christian Traxler, Gabriel Ulyssea, Stijn Van Nieuwerburgh, Emil Verner, Thomas Winberry, Ming Xu, Pierre Yared for helpful comments. We also thank seminar participants at Frankfurt School of Finance & Management, Boston University, Banco de Portugal, INSEAD, Johns Hopkins University, University of Maryland, the Federal Reserve Bank of Chicago, University of Duisburg-Essen, Humboldt University of Berlin, ESSEC, Sciences Po, University of Cambridge, Copenhagen Business School, Columbia University, EIEF Rome, and conference participants at the 2018 Mitsui Finance Symposium, the 2018 SED Annual Meeting, the 2018 UBC Summer Finance Conference, the 2018 German Economic Association Annual Meeting, the 2018 Endless Summer Conference on Financial Intermediation and Corporate Finance, the 2019 SOLE Annual Meeting, the 2019 Barcelona GSE Summer Forum, the 2020 Econometric Society North American Winter Meeting, and the 2020 Conference on Firm Heterogeneity and the Macroeconomy (virtually) in Oxford for many helpful suggestions. Brenden Eum and Rachel Williams provided excellent research assistance. A previous version of this paper circulated under the title "The Effects of Credit Supply on Wage Inequality between and within Firms." The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. Any errors are our own.

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1 Introduction

A salient characteristic of many labor markets is that seemingly identical workers receive substantial differences in pay across employers. Motivated by this observation, a burgeoning literature has explored the contribution of employer heterogeneity toward empirical pay dispersion.[1] A recent strand of this literature has linked *changes* in the earnings distribution to *changes* in within- and between-employer pay differences.[2] Yet the fundamental drivers of (changes in) within- and between-employer pay differences remain scarcely understood.

A common explanation for the existence of employer pay differences pertains to firm-specific labor demand. In theory, differences in labor demand across firms in a frictional labor market can give rise to wage dispersion for identical workers—a deviation from the law of one price in competitive labor markets. In practice, however, the labor demand channel of firm pay heterogeneity is hard to pinpoint empirically due to two challenges. First, measures of firm pay may be confounded by worker composition that is undetectable absent individual-level panel data. Second, the effect of firm-specific labor demand on pay is difficult to disentangle from competing explanations such as labor supply heterogeneity, absent identified variation in labor demand.[3]

In this paper, we study the wage and employment effects of changes in labor demand due to a firm-level credit supply shock. In doing so, we address the two aforementioned empirical challenges. Specifically, we construct a novel dataset that links worker employment histories to firms' bank credit relationships in Germany. We exploit as a source of variation in credit supply the introduction of negative monetary policy rates by the European Central Bank (ECB) in 2014. We show that firms in preexisting relationships with banks that were more exposed to negative rates see a relative reduction in credit. Less credit in turn is associated with lower firm-level average wages and employment. These effects are concentrated among distinct worker groups within firms. Initially lower-paid workers are more likely to be fired, while initially higher-paid workers see relative wage declines. At the same time, wages fall by more at initially higher-paying firms. Consequently, wage inequality within and between firms decreases. In summary, we find that a monetary policy-induced firm-level credit supply shock affects the distribution of pay and employment, consistent with the labor demand channel in a frictional labor market.

To guide our empirical investigation, we develop an equilibrium model with both credit fric-

[1] For a recent literature survey, see Card et al. (2018).

[2] See the evidence by Card et al. (2013) for Germany, Alvarez et al. (2018) for Brazil, and Song et al. (2019) for the U.S.

[3] Firms could face heterogeneous labor supply curves due to, for example, local labor market concentration (Berger et al., 2019; Hershbein et al., 2020) or the presence of job amenities (Sorkin, 2018; Lamadon et al., 2019).

tions and search frictions. We extend the seminal framework by Burdett and Mortensen (1998) to include worker heterogeneity in skills and firm heterogeneity in credit constraints. Firms with different productivities use debt to finance their operating costs subject to firm-specific borrowing limits. Firms' labor demand depends on their productivity and the tightness of their credit constraint. A tightening of a firm's credit constraint reduces labor demand, leading to lower wages and employment for both high-skill and low-skill workers. If wages are relatively rigid for low-skill workers, for example due to a binding wage floor, then credit tightening causes the wages of high-skill workers to decline more than those of low-skill workers, and more so at initially higher-paying firms. As a result, both within- and between-firm wage inequality decrease.

Guided by these model predictions, we study the effect of a monetary policy-induced firm-level credit supply shock on individual wages and employment in the data. To identify firm-level variation in credit supply, our empirical strategy exploits the heterogeneous transmission of negative monetary policy rates to bank lending through banks' funding structure as highlighted by Heider et al. (2019). The introduction of negative rates constitutes a credit supply shock as banks are reluctant, or unable, to pass on negative rates to their depositors. More deposit-reliant banks experience relatively higher funding cost and reduce lending by relatively more due to negative rates. To study the distributional effects of credit supply in the labor market, our empirical investigation uses this variation in two stages.

In the first stage of our empirical investigation, we show that firms in preexisting relationships with deposit-reliant banks experience a credit supply shock due to the introduction of negative rates. More affected firms see a relative reduction in credit, both along the extensive margin—receiving any loan—and along the intensive margin—loan volume. These results are robust to controlling for bank-firm match-specific and time-varying bank-specific unobserved heterogeneity, which subsumes aggregate economic conditions and variation in banks' financial health during this period. We find that more affected firms reduce their leverage by more, suggesting that they are unable to fully substitute credit by switching banks or accessing other debt sources. They also increase their cash holdings, consistent with precautionary savings. At the same time, we find no significant changes in firms' fixed assets, suggesting sizable capital adjustment costs.

In the second stage of our empirical investigation, we study the effect of this firm-level credit supply shock on individual wages and employment. To this end, we exploit the granularity of the German linked employer-employee data merged with information on firms' banking relationships. In line with our model predictions, we find that the credit contraction due to the introduction of negative monetary policy rates leads to lower firm-level average wages and employment. A one standard deviation increase in exposure to the negative credit supply shock is associated with a significant reduction in mean wages of up to 1.3 percent, and a significant increase in layoff risk of up to 0.2 percentage points. These estimates control for worker-firm match heterogeneity and state time trends. Absent individual-level micro data, these effects would be confounded by changes in workforce composition due to worker turnover.

The estimated mean effects of the negative credit supply shock on wages and employment mask important heterogeneity across worker groups *within* firms. To shed light on this heterogeneity, we estimate individual wage equations with controls for worker-firm match-specific and time-varying firm pay components. We find that initially lower-paid workers are more likely to be fired, while initially higher-paid workers see relative wage declines. A one standard deviation increase in exposure to the negative credit supply shock is associated with a significant reduction in top-quintile wages of around 0.8 percent relative to workers in the bottom quintile. At the same time, layoff risk for bottom-quintile workers increases significantly by around 0.2 percentage points per standard deviation of exposure relative to workers in the top quintile. Consequently, *within*-firm wage inequality decreases.

We also find important effects of the negative credit supply shock on the distribution of wages *between* firms. To demonstrate this, we estimate a specification including an interaction term with a firm's initial pay rank in addition to controls for worker-firm match heterogeneity and state time trends. Our estimates suggest that among firms affected by the credit supply shock, wages decline more at initially higher-paying firms, with wages at top-ranked firms falling by up to 14 percent relative to bottom-ranked firms, while the layoff risk at bottom-ranked firms is around 2 percentage points higher than at top-ranked firms. Consequently, *between*-firm inequality decreases.

In summary, our analysis yields two novel insights. Our first insight is that credit supply affects pay *within and between* firms. This finding is at odds with models of competitive labor markets in which workers' wages equal their marginal product regardless of their employer's idiosyncratic credit constraints.[4] Our second insight is that monetary policy-induced credit supply has important distributional consequences in the labor market. In contrast, traditional research on monetary policy focuses on its effect on the level—i.e., the first moment—of output, employment, and prices. Both of these insights are consistent with the labor demand channel of firm pay heterogeneity at the heart of our equilibrium model.

[4]See Jermann and Quadrini (2012), Moll (2014), and Kiyotaki and Moore (2019) for examples of such models.

Related Literature. Our work relates to three strands of the literature. The first strand of the literature studies pay dispersion within and between firms. Motivated by the fact that observationally identical workers receive large differences in pay across industries (Dickens and Katz, 1987; Krueger and Summers, 1988), numerous studies have highlighted the role of employer heterogeneity in explaining empirical wage dispersion. Abowd et al. (1999) develop and apply to French administrative data a two-way fixed effects model, which simultaneously controls for unobserved worker and firm heterogeneity. Since then, robust evidence of employer pay heterogeneity has been found in several countries.[5] Our findings contribute to this literature by shedding light on the fundamental *drivers* of the within- and between-firm pay structure. To the extent that over the past decades Germany has seen an increase in credit supply, our findings suggest that changes in firm credit-induced labor demand could explain part of the rise in wage inequality (Dustmann et al., 2009; Card et al., 2013; Lochner et al., 2020) and the fall in the labor share (Karabarbounis and Neiman, 2013; Autor et al., 2020) over this period.

The existence of firm pay differences for identical workers poses a challenge to models of competitive labor markets, in which the law of one price holds. To rationalize firm pay differences, a large theoretical literature in the tradition of Burdett and Mortensen (1998) has developed frictional equilibrium models, which have inspired empirical work by Manning (2003, 2011), among others.[6] In these models, firm productivity differences generate heterogeneous firm labor demand and equilibrium firm pay differences. The labor demand channel is also central to understanding equilibrium unemployment over the business cycle (Shimer, 2005) and the impact of policies such as unemployment insurance (Hagedorn et al., 2019). Fewer papers consider the role of firm credit in determining employment and pay through the labor demand channel in a frictional market. In this regard, closest to our theoretical framework are those by Wasmer and Weil (2004) and Kehoe et al. (2019, 2020). Like them, we introduce credit frictions into a search-and-matching environment. Unlike them, we model multi-worker firms, which allows us to study the effect of credit supply on both within- and between-firm differences in pay and employment.

The second strand of the literature concerns the empirical regularity that employers imperfectly insure workers against idiosyncratic shocks. Guiso et al. (2005) estimate positive passthrough of permanent firm productivity shocks to workers, and more so to managers. Fagereng et al.

[5] These include Italy (Iranzo et al., 2008), the U.K. (Faggio et al., 2010), Germany (Goldschmidt and Schmieder, 2017), Brazil (Lopes de Melo, 2018), Mexico (Frías et al., 2018), Portugal (Card et al., 2016), Sweden (Håkanson et al., forthcoming), and the U.S. (Barth et al., 2016; Sorkin, 2018; Babina et al., 2019).

[6] For recent examples, see Engbom and Moser (2018), Bagger and Lentz (2019), Heise and Porzio (2019), and Morchio and Moser (2020).

(2018) find greater passthrough of productivity shocks to workers with higher wealth. Several other studies have focused on passthrough of shocks to productivity,[7] innovation,[8] and taxes.[9] A novel aspect of our work is our focus on passthrough of firm credit. Our estimates are consistent with previous studies of passthrough in that we find positive wage sensitivity to credit and greater sensitivity among higher-ranked workers. In related work, Michelacci and Quadrini (2009) and Guiso et al. (2013) show that firm credit affects starting wages and wage growth of new hires. Benmelech et al. (2012) study wage concessions of workers at airlines under financial distress due to bankruptcy. Bloom et al. (2017) link individual wage volatility to firm-level employment volatility. Bagger et al. (2020) study the transmission of productivity shocks to vacancy postings across firms. Our work complements theirs by demonstrating that shocks to firm credit have different effects on wages and employment throughout the within- and between-firm distribution.

The third strand of the literature concerns the distributional effects of monetary policy. Credit supply is a key pillar of the credit channel of monetary policy (Gertler and Kiyotaki, 2010) and is empirically relevant for several macroeconomic outcomes.[10] Previous work by Doepke and Schneider (2006), Kumhof et al. (2015), Coibion et al. (2017), and Holm et al. (2020) has linked inequality to monetary policy and *household* finances. Our paper is among the first to identify *firm* credit as a source of labor market inequality through its effect on the distribution of wages within and between employers. This complements prior studies of the effect of credit on employment at the firm level (Chodorow-Reich, 2014; Jiménez et al., 2017) and across skills groups within firms (Berton et al., 2018; Barbosa et al., 2020). While it is important to measure employment, as we do in our own analysis, understanding the effects of credit on pay matters for the vast majority of workers who do not change employment status. A small number of concurrent papers measure the responsiveness of worker-level wages to firm-level credit shocks (Hochfellner et al., 2015; Fonseca and Van Doornik, 2019; Adamopoulou et al., 2020). A distinguishing feature of our work is that we study the effects of a monetary policy shock and that we focus on the distribution of wages within and between firms. Thus, our results shed new light on the distributional consequences of monetary policy, which have been the subject of a new generation of empirically-oriented models.[11]

[7]See Friedrich et al. (2019), Lamadon et al. (2019), Engbom and Moser (2020), and Chan et al. (2020).

[8]See Van Reenen (1996), Kline et al. (2019), Aghion et al. (2019), Howell and Brown (2020), and Kogan et al. (2020).

[9]See Arulampalam et al. (2012), Suárez Serrato and Zidar (2016), and Fuest et al. (2018).

[10]These include investment (Amiti and Weinstein, 2018), productivity (Gilchrist et al., 2013), employment (Chodorow-Reich, 2014), innovation (Huber, 2018), demand (Mian et al., 2020), and firm dynamics (Acabbi et al., 2020).

[11]See Gornemann et al. (2016), McKay and Reis (2016), Kaplan et al. (2018), Auclert (2019), Bilbiie (2019), Ravn and Sterk (2020), Acharya et al. (2020), Auclert et al. (2020), Kekre and Lenel (2020), and Ottonello and Winberry (2020).

Outline. The remainder of the paper is structured as follows. Section 2 develops an equilibrium model of firm credit in a frictional labor market. Section 3 outlines our empirical strategy. Section 4 discusses the data. Section 5 presents our empirical results. Finally, Section 6 concludes.

2 Equilibrium Model of Wage Dispersion with Credit Frictions

The purpose of this model is to theoretically link credit supply to the distribution of wages and employment within and between firms. Motivated by the empirical observation that identical workers receive different pay across employers in Germany (Card et al., 2013), we model the labor market as frictional, as in the seminal framework by Burdett and Mortensen (1998). We extend this framework to include worker heterogeneity in skills and firm heterogeneity in credit constraints.

2.1 Economic Environment

A mass 1 of workers and mass E of firms meet in a frictional labor market set in continuous time.

2.2 Workers

Workers are infinitely lived, risk neutral, and discount the future at rate ρ. They differ in permanent skill $a \in \{a_L, a_H\}$. We assume $0 < a_L < a_H$ and refer to worker types as low-skill and high-skill, with population shares μ_a. Workers find themselves either employed or unemployed.

Job search. Unemployed workers receive flow utility b_a, with $0 < b_{a_L} < b_{a_H}$, and engage in random job search within labor markets segmented by worker type a. Search is random in the sense that workers cannot direct their search to specific firms. Labor markets are segmented in the sense that workers search for jobs in a market specific to their type, while firms post wages and vacancies for each worker type. While employed, workers receive flow utility from their wage w and engage in on-the-job search within their assigned labor market.

Unemployed workers receive job offers at endogenous rate λ_a^u and employed workers at rate $\lambda_a^e = s_a^e \lambda_a^u$, where s_a^e is the relative on-the-job search intensity, which we assume is fixed and satisfies $s_{a_L}^e = 0 < s_{a_H}^e \leq 1$. A job offer entails a wage w drawn from the distribution $F_a(w)$, which workers take as given but is determined endogenously through firms' equilibrium decisions.

Jobs are terminated exogenously at rate δ_a, leaving workers unemployed. For low-skill employed workers, this is the only source of employment transitions. High-skill workers also separate endogenously when offered a higher-wage job.

Employer ranks. Workers rank jobs on a ladder according to their expected net present value of wages. In equilibrium, low-skill workers draw wages from a degenerate offer distribution concentrated on their reservation wage and cannot transition directly between jobs, as in Diamond (1971). High-skill workers are mobile between jobs and rank employers according to their wage.

Value functions. The value of an employed worker of ability a in a job with wage w is

$$\rho S_a(w) = w + \lambda_a^e \int_{w'>w} \left[S_a(w') - S_a(w)\right] dF_a(w') + \delta_a \left[W_a - S_a(w)\right], \quad \forall a. \tag{1}$$

The value of an unemployed worker of type a is

$$\rho W_a = b_a + \lambda_a^u \int_{w'} \max\left\{S_a(w') - W_a, 0\right\} dF_a(w'), \quad \forall a. \tag{2}$$

Policy functions. Employed workers accept any job with a higher wage. Unemployed workers' optimal job acceptance policies follow a threshold rule. Their reservation wage equals their flow value of unemployment plus the forgone option value of receiving job offers while unemployed:

$$\phi_a = b_a + (\lambda_a^u - \lambda_a^e) \int_{w'\geq\phi_a} \frac{1 - F_a(w')}{\rho + \delta_a + \lambda_a^e\left[1 - F_a(w')\right]} dw', \quad \forall a. \tag{3}$$

We assume that ϕ_{a_L} and ϕ_{a_H} are low enough so that all firms hire both skill types.

Unemployment. The steady-state unemployment rate for each worker type is

$$u_a = \frac{\delta_a}{\delta_a + \lambda_a^u}, \quad \forall a. \tag{4}$$

Wage dispersion. Let $\kappa_a^e = \lambda_a^e/\delta_a$ govern the effective speed of workers climbing the job ladder. The cross-sectional distribution of wages is $G_a(w) = F_a(w)/[1 + \kappa_a^e[1 - F_a(w)]$.

2.3 Firms

Firms differ in two dimensions: productivity $p \in [\underline{p}, \overline{p}] \subset \mathbb{R}_{++}$ and credit limit $\xi \in [\underline{\xi}, \overline{\xi}] \subset \mathbb{R}_{++}$. We assume firm types $j = (p, \xi)$ are distributed continuously according to $\Gamma(j)$. With a slight abuse of notation, we index firms, their productivity, and their credit limit by j.

Wages and job vacancies. Firms post in each market a wage rate w_a and job vacancies v_a subject to flow cost $c_a(v_a)$, where $c_a(\cdot)$ satisfies $c_a(0) = 0$, $\partial c_a(0)/\partial v = 0$, $\partial c_a(v)/\partial v, \partial^2 c_a(v)/\partial v^2 > 0$ for all $v > 0$, and $\lim_{v \to +\infty} \partial c_a(v)/\partial v = +\infty$.

Production. A firm with productivity p_j employing $\{l_a\}_{a \in \{a_L, a_H\}}$ workers of each skill level produces output $y(p_j, \{l_a\}_{a \in \{a_L, a_H\}}) = p_j \sum_{a \in \{a_L, a_H\}} a l_a$ by combining different worker types.[12]

Credit constraint. Firms take up debt $D \in \mathbb{R}_+$ to finance their operating costs before production occurs, as in Christiano et al. (2005) or Acabbi et al. (2020). Operating costs consist of the wage bill and recruiting costs, so $\sum_{a \in \{a_L, a_H\}} [w_a l_a + c_a(v_a)] \leq D$.[13] Firms take as given the exogenous interest rate r and face idiosyncratic credit limits given by $rD \leq \xi_j$.

Value function. The value of a firm of type $j = (p_j, \xi_j)$ is the net present value of revenues minus the wage bill minus recruiting costs minus the cost of servicing debt, which can be written as

$$\rho \Pi(j) = \max_{\{w_a, v_a\}_{a \in \{a_L, a_H\}}} \left\{ \sum_{a \in \{a_L, a_H\}} \left[\left(p_j a - (1+r) w_a\right) l_a(w_a, v_a) - (1+r) c_a(v_a) \right] \right\} \tag{5}$$

$$\text{s.t.} \quad r \sum_{a \in \{a_L, a_H\}} [w_a l_a(w_a, v_a) + c_a(v_a)] \leq \xi_j.$$

2.4 Matching and Firm Sizes

The effective mass of job searchers in market a equals

$$U_a = \mu_a \left[u_a + s_a^e (1 - u_a)\right], \quad \forall a. \tag{6}$$

The mass of vacancies posted in market a across firm types j is given by

$$V_a = E \int_j v_a(j) \, d\Gamma(j), \quad \forall a. \tag{7}$$

[12]The assumption of linearity in production within and across worker types simplifies the analysis but is not crucial. In theory, it could be relaxed to allow for decreasing returns in each worker type and complementarity between types.

[13]Our fundamental insights are unchanged in a model extension with capital and other inputs entering production subject to a credit constraint. This modeling choice is partly informed by our empirical finding that there is little change in capital (fixed assets) associated with a credit supply shock of the size that we study.

A Cobb-Douglas matching function with constant returns to scale combines the effective mass of job searchers with the mass of job vacancies to produce, for each a, matches $m_a = \chi_a V_a^{\alpha} U_a^{1-\alpha}$, with matching efficiency $\chi_a > 0$ and elasticity $\alpha \in (0,1)$. Define labor market tightness as

$$\theta_a = \frac{V_a}{U_a}, \quad \forall a. \tag{8}$$

Job finding rates among unemployed and employed workers, and firms' job filling rates are

$$\lambda_a^u = \chi_a \theta_a^{\alpha}, \qquad \lambda_a^e = s_a \lambda_a^u, \qquad q_a = \chi_a \theta_a^{\alpha-1}, \quad \forall a. \tag{9}$$

The following Kolmogorov forward equation describes firms' employment given wage and vacancy policies (w, v), the offer distribution $F_a(w)$, and market tightness θ_a in steady state:

$$l_a(w,v) = \left(\frac{1}{\delta_a + \lambda_a^e \left[1 - F_a(w)\right]} \right)^2 \frac{1}{V_a} \mu_a u_a \lambda_a^u \left(\delta_a + \lambda_a^e\right) v, \quad \forall a. \tag{10}$$

2.5 Equilibrium Labor Demand

We define a *stationary equilibrium* of the economy in Appendix A.1. A firm's equilibrium labor demand manifests itself in two choice variables: a wage and a mass of vacancies for each worker skill. Firms' optimal wage and vacancy policies depend on their productivity but also take into account the shadow cost of funds to pay their wage bill and recruiting costs subject to a credit constraint. Firm optimality requires the following first-order conditions (FOCs) to hold:

$$[\partial w_a]: \quad p_j a \frac{\partial l_a\left(w_a, v_a\right)}{\partial w_a} - \left(1 + (1+\psi_j) r\right) \left[l_a\left(w_a, v_a\right) + w_a \frac{\partial l_a\left(w_a, v_a\right)}{\partial w_a} \right] = 0, \quad \forall a, \tag{11}$$

$$[\partial v_a]: \quad p_j a \frac{\partial l_a\left(w_a, v_a\right)}{\partial v_a} - \left(1 + (1+\psi_j) r\right) \left[w_a \frac{\partial l_a\left(w_a, v_a\right)}{\partial v_a} + \frac{\partial c_a\left(v_a\right)}{\partial v_a} \right] = 0, \quad \forall a, \tag{12}$$

where $\psi_j \geq 0$ is the shadow cost of resources associated with firm j's credit constraint. For unconstrained firms, $\psi_j = 0$, while for credit constrained firms, $\psi_j > 0$. Firms are more likely to be credit constrained if they have higher productivity for a given credit limit or, alternatively, if they have a lower credit limit for a given productivity. When their credit constraint binds, firms follow different wage and vacancy policies than they would if they were unconstrained.

The FOCs in equations (11) and (12) are identical to those of a firm with *effective productivity*

$$\tilde{p}_j = p_j \frac{1+r}{1+(1+\psi_j)r}. \tag{13}$$

Note that $\tilde{p}_j = p_j$ for unconstrained firms with $\psi_j = 0$, while $\tilde{p}_j < p_j$ for credit constrained firms with $\psi_j > 0$. Firms facing a tighter credit constraint, as measured by ψ_j, have lower effective productivity due to the higher shadow cost of resources.

An argument analogous to that in Burdett and Mortensen (1998) shows that equilibrium wages for high-skill workers are strictly increasing in effective productivity $\tilde{p}_j$, and the equilibrium offer distribution $F_{a_H}(w)$ is continuous and strictly increasing for $w > \max\{\underline{p}a_H, \phi_{a_H}\}$. For high-skill workers, firms find themselves ranked on a ladder according to their effective productivity $\tilde{p}_j$, which is increasing in their productivity p_j and decreasing in the tightness of their credit constraint as measured by ψ_j.[14]

Lemma 1 (Optimal wage policy)**.** *Optimal high-skill wages, w_{a_H}, are strictly increasing in productivity p_j and strictly increasing (constant) in the credit limit ξ_j for credit constrained (unconstrained) firms. Optimal low-skill wages, w_{a_L}, are constant and equal to their flow value of unemployment, b_{a_L}.*

Proof. See Appendix A.2.1. □

The intuition behind Lemma 1 is that the payoff from hiring is greater for more productive and less credit constrained firms. Since higher wages attract and retain high-skill workers, they are increasing in productivity and in the credit limit for constrained firms. Low-productivity workers' wages are not allocative, so their wages are invariant to productivity and the credit limit. Therefore, while low-skill workers wages respond one-for-one to their reservation wage, high-skill workers are partly shielded from the value of nonemployment, as in Jäger et al. (forthcoming).

Lemma 2 (Optimal vacancy policy)**.** *Optimal low-skill vacancies, v_{a_L}, and high-skill vacancies, v_{a_H}, are strictly increasing in productivity p_j and strictly increasing (constant) in the credit limit ξ_j for credit constrained (unconstrained) firms.*

Proof. See Appendix A.2.2. □

The intuition behind Lemma 2 is that productivity and credit limits increase the payoff from

[14] Furthermore, firm profits are increasing in effective productivity (Bontemps et al., 2000), the distribution of which also affects the aggregate labor share (Gouin-Bonenfant, 2020).

hiring. Since firms equate the marginal cost of vacancy posting to the marginal profit per contacted worker, firms with higher productivity and higher credit limits post more vacancies.

Lemma 3 (Optimal employment)**.** *Optimal low-skill employment, l_{a_L}, and high-skill employment, l_{a_H}, are strictly increasing in productivity p_j and strictly increasing (constant) in the credit limit ξ_j for credit constrained (unconstrained) firms.*

Proof. See Appendix A.2.3. □

Lemma 3 follows directly from Lemmas 1 and 2 given the model's job ladder structure. Higher-wage firms poach more and lose fewer workers through job-to-job transitions, while higher-vacancy firms recruit more workers from unemployment and from other firms.[15]

2.6 Equilibrium Wage Dispersion within and between Firms

How do credit supply-induced changes in firms' labor demand affect the distribution of wages within and between firms? The following proposition compares firms across steady states of the economy with different levels of credit supply.

Proposition 1 (Within- and between-firm inequality)**.** *A decrease in the credit limit ξ_j for all j leads to*

(a) lower within-firm pay inequality, measured by the top-to-bottom difference in wages within firms, and

(b) lower between-firm pay inequality, measured by the top-to-bottom difference in mean wages between firms conditional on worker composition.

Proof. See Appendix A.2.4. □

The intuition behind Proposition 1 is as follows. For part (a), if low-skill wages are relatively more downward rigid than high-skill wages are, then within-firm inequality is decreasing in the tightness of credit constraints. For part (b), holding fixed worker composition across firms, an analogous reasoning implies that mean wages of firms initially at the top of the distribution decrease by more than those at the bottom.[16]

[15] While the relative employment effect on high-skill versus low-skill workers is theoretically ambiguous, a natural hypothesis is that employment responds more for low-skill jobs whose surplus is likely closer to zero, as in Hagedorn and Manovskii (2008).

[16] A similar result applies unconditional on worker composition when holding fixed job offer arrival rates $\{\lambda_a^u, \lambda_a^e\}$ for both a or, alternatively, for a high enough hiring cost elasticity.

2.7 Testable Predictions

The theoretical model has clear predictions for the distribution of wage and employment effects of credit supply across firms in the labor market. In summary, a tightening of credit supply

1. reduces mean wages and employment,
2. reduces within-firm pay inequality, and
3. reduces between-firm pay inequality.

As the comparative statics results pertain to two steady states, pay and employment at continuing firms are expected to adjust over time following a negative credit supply shock. On the one hand, the real value of pay may adjust immediately through nominal wage cuts or more slowly by freezing nominal wages in the presence of inflation.[17] On the other hand, employment may adjust immediately by firing existing workers or more slowly by reducing new hires.[18] What the modalities and magnitude of these model predictions are is ultimately an empirical question. In what follows, we test these predictions using an identified credit supply shock together with microdata on worker employment histories and firms' bank credit relationships in Germany.

It is worth noting that the predictions of our model with credit frictions *and* search frictions are markedly different from classical models of credit constraints with comptitive labor markets. In these models, within-firm pay differences derive only from ability differences and the same worker gets paid identically across employers, regardless of firm credit constraints. In contrast, our model generates equilibrium wage dispersion within and between firms that depends on the distribution of credit supply.

3 Empirical Strategy

Guided by the predictions of the model from the previous section, our goal is to estimate the effect of credit supply on the distribution of pay and employment within and between firms. Before going into details of the specific empirical setting based on which we identify variation in credit supply, it will be useful to spell out the general methodology that allows us to achieve our goal.

[17] Adjustments in real wages may be slow due to nominal wage rigidities, imposed by collective bargaining agreements or otherwise, for incumbents or new hires (Schoefer, 2015; Hazell and Taska, 2019).

[18] While firing restrictions are still significant in Germany, its labor market institutions have become increasingly flexible and decentralized since the early 2000s (Dustmann et al., 2014).

3.1 Measuring the Effects of Credit Supply within and between Firms

Consider a panel of workers indexed by i across firms indexed by j and years indexed by t. Our goal is to track pay and employment of workers in the labor market following a credit supply shock to differentially affected firms. Let us denote such a shock to credit supply at the level of the firm-year jt by $Credit_{jt}$.

Mean effects. While the credit supply shock is at the firm-year level, we study individual pay and employment at the level of the worker-firm-year ijt. Our simplest specification will be:

$$y_{ijt} = \beta Credit_{jt} + \theta_{ij} + \zeta_{st} + \varepsilon_{ijt}, \tag{14}$$

where y_{ijt} is an outcome for worker i at firm j in year t, $Credit_{jt}$ is the credit supply shock described above, and θ_{ij} and ζ_{st} denote, respectively, worker-firm and state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in. The coefficient of interest in equation (14) is β, which measures the average response of y_{ijt} to variation in $Credit_{jt}$. By controlling for worker-firm match fixed effects, we identify this coefficient off the effect on workers that were already employed at the same firm prior to the credit supply shock. By additionally controlling for state-year fixed effects, we absorb aggregate trends and regional business cycle fluctuations that affect equally all workers in a given state.

Aside from the credit supply shock's mean effect on workers, we are also interested in its distributional effects. Specifically, we study the effect of credit on the distribution of worker-level outcomes within and between firms.

Within-firm heterogeneity. To estimate *within*-firm heterogeneity in the effect of credit, we interact the credit supply shock with a function of a worker's pay rank within the firm:

$$y_{ijt} = \beta_1 Credit_{jt} \times RankWithin_i + \beta_2 Credit_{jt} + \beta_3 RankWithin_i + \theta_{ij} + \eta_{jt} + \varepsilon_{ijt}, \tag{15}$$

where $RankWithin_i$ is a function of worker i's pay rank within firm j during a preperiod prior to the credit supply shock, and θ_{ij} and η_{jt} denote worker-firm and firm-year fixed effects, respectively. The coefficient of interest in equation (15) is β_1, which measures the differential response of y_{ijt} to variation in $Credit_{jt}$ throughout the within-firm pay distribution. As before, by controlling for worker-firm match fixed effects, we identify this coefficient off the effect on workers that were already employed at the same firm prior to the credit supply shock. In addition to the set of previous controls, we also add a set of firm-year fixed effects that control for time-varying unobserved heterogeneity at the firm level that may govern firm-level movements in pay or employment. This powerful control absorbs, for instance, aggregate trends and idiosyncratic firm innovations, including productivity shocks and other factors that affect all workers within a given firm equally.

Between-firm heterogeneity. To estimate *between*-firm heterogeneity in the effect of credit, we interact the credit supply shock with a function of a firm's mean pay rank:

$$y_{ijt} = \beta_1 Credit_{jt} \times RankBetween_j + \beta_2 Credit_{jt} + \beta_3 RankBetween_j + \theta_{ij} + \zeta_{st} + \varepsilon_{ijt}, \tag{16}$$

where $RankBetween_j$ is a function of firm j's mean pay rank during a preperiod prior to the credit supply shock, and θ_{ij} and ζ_{st} denote, respectively, worker-firm and state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in. The coefficient of interest in equation (16) is β_1, which measures the differential response of y_{ijt} to variation in $Credit_{jt}$ throughout the firm pay distribution.

Firm-level aggregation. In addition to our worker-level analysis of the effects of credit, we are also interested in outcomes aggregated to the firm level. To study such outcomes, we explicitly allow for changes in worker composition due to separations and hires, which we previously held constant when including worker- or worker-firm match-specific controls. To ascertain the effect of credit supply on firm-level outcomes, we estimate the following specification:

$$y_{jt} = \beta Credit_{jt} + \psi_j + \zeta_{st} + \varepsilon_{jt}, \tag{17}$$

where y_{jt} is an outcome for firm j in year t, ψ_j denotes firm fixed effects, and ζ_{st} are state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in.

3.2 Identification

To study the firm-level and worker-level effects of credit, the ideal experiment would involve manipulating the credit supply to a known subset of firms but not others in a "macroeconomic laboratory." Absent this ideal variation, we exploit a quasi-natural experiment that involves firm-level variation in credit supply. Specifically, we study the heterogeneous transmission of monetary policy to bank lending following the unanticipated implementation of negative *deposit facility rates* in the euro area. We show that, depending on firms' preexisting bank relationships and banks' balance sheet exposure to negative rates, this episode resulted in firm-level variation in credit supply.

The deposit facility rate is the rate at which banks may make overnight deposits with the Eurosystem, i.e., the ECB and national central banks of countries that have adopted the euro currency. It is one of three main policy rates set by the Governing Council of the ECB.[19] By affecting the return on bank deposits, the deposit facility rate is a key determinant of deposit-reliant banks' funding cost and hence their lending activity.

In June 2014, for the first time in the history of the euro, the deposit facility rate was set to negative. There is broad consensus that this unprecedented step came as a surprise to financial institutions and firms, as evidenced by the sharp market reaction and ensuing devaluation of the euro currency (Hirst, 2014). Since then, the deposit facility rate has remained negative. Figure 1 shows the deposit facility rate over our period of study between January 1, 2010 and December 31, 2017. Our identification strategy exploits heterogeneous effects of this negative rate episode.

During normal times, the deposit facility rate has little bite when banks can pass on positive rates to their clients. As such, lowering monetary policy rates decreases banks' funding cost independent of their financing structure, which induces them to increase lending to firms in line with classical monetary theory (Gertler and Kiyotaki, 2010). Exploiting such fluctuations in the level of credit supply due to changes in positive rates would be fruitful in theory. However, due to their aggregate nature, monetary policy-induced credit supply shocks are difficult to disentangle empirically (Nakamura and Steinsson, 2018).

Instead, our identification strategy exploits cross-sectional variation in banks' funding cost due to imperfect passthrough of monetary policy to deposit rates, akin to Drechsler et al. (2017). Specifically, we exploit that banks are reluctant, or unable, to pass on negative rates to their depositors. As a result, banks with greater reliance on deposit funding experience relatively greater funding cost that results in a reduction in lending, as documented for the euro area (Heider et al., 2019) and for Sweden (Eggertsson et al., 2019). To the extent that banking relationships are sticky (Chodorow-Reich, 2014; Darmouni, forthcoming), this leads firms in preexisting relationships with more deposit-reliant banks to experience a relative contraction in credit supply.

[19]The other two policy rates are the *main refinancing operations rate*, which determines the cost at which banks can engage in one-week borrowing, and the *marginal lending facility rate*, which determines the cost at which banks can engage in overnight borrowing from the Eurosystem.

Given that negative monetary policy rates lead to a differential *financial* shock across banks, as documented using syndicated loan-level data by Heider et al. (2019), we explore to what degree this episode also resulted in a differential *real* shock to firms and their employees. We extend existing work in four important dimensions. First, we study private and public firms in Germany without the restriction to bank-firm relationships in the syndicated loans market. This allows us to cover a significantly larger fraction of firms and workers, since syndicated loans are almost exclusively accessed by large corporations. Second, we aggregate the effects of exposure to negative rates to the firm level. Firm-level aggregation is important because firms may be able to partly offset loan-level shocks by substituting across financing sources. Third, we examine the effects of credit supply on both financial and real variables. Although the real outcomes of monetary policy-induced credit supply are of direct interest, some real variables (e.g., capital) may be sluggish to react to credit in the presence of adjustment costs, rendering the magnitude of their response an empirical question. Fourth, we link variation in credit supply to worker-level outcomes, including individual pay and employment. By analyzing worker-level panel data, we are able to study the distributional consequences of a monetary policy-induced credit supply shock.

We use this credit supply shock as follows. As a firm's exposure to negative rates depends on its bank relationships, we categorize firms according to their relations on deposit-reliant banks. For this purpose, we combine data on firms' self-reported banking relationships with bank-level balance sheet information. Specifically, let $\textit{Deposit ratio}_j$ denote the average deposit ratio, that is the ratio of deposits to assets, across all (typically German) euro-area banks that firm j reports to be in a banking relationship with during the preperiod from 2010 to 2013. Let $\textit{After}(2014)_t$ denote a dummy variable for the years 2014–2017. Then, following the argument above, we define as our credit supply shock proxy the following:

$$\textit{Credit}_{jt} \equiv \textit{Deposit ratio}_j \times \textit{After}(2014)_t. \tag{18}$$

The proxy in equation (18) captures the idea that firms in relationships with banks, which were more affected by negative rates after June 2014 through greater reliance on deposit funding, experienced a negative credit supply shock.

3.3 Specification Details

We consider individual pay and employment as outcome variables associated with specifications (14)–(16), which are concerned with the worker-level effects of credit supply. Specifically, we consider for each individual their log wage and an indicator for whether they are no longer employed next year. For the firm-level aggregate specification (17), we consider as outcome variables various inequality measures, such as the log P90-P10 wage percentile ratio, and employment counts, such as the log number of employees.

In the within-firm specification (15), we replace $RankWithin_i$ by an indicator for the position in the wage distribution at firm j where worker i was found in the last available year during the preperiod 2010–2013. Specifically, we split the within-firm wage distribution into three parts. We add to our specification indicators for the bottom wage quintile (*Bottom 20% within firm*$_i$) and the center quintiles (*Middle 60% within firm*$_i$), leaving the top quintile (*Top 20% within firm*$_i$) as the omitted category.

In the between-firm specification (16), we replace $RankBetween_j$ by a continuous variable *Firm pay rank*$_j$ that lies between 0 and 1, with 0 representing the firm with the lowest and 1 representing that with the highest mean wage in the last year prior to the introduction of negative rates (2013).

Finally, we cluster standard errors at the firm level throughout since we exploit variation in firm-level exposure to a bank-specific lending shock.

4 Data

4.1 Data Sources

For the first time, this paper combines multiple datasets spanning the complete credit chain in Germany: starting from banks' balance sheet exposure to monetary policy, to bank-firm relationships and loan transactions, to firm financials, and finally to worker-level outcomes. Building this data infrastructure requires us to combine microdata from several different data providers, including private and restricted public data sources.

Employment histories (IAB). At the heart of our analysis lie the administrative linked employer-employee data hosted at Germany's Institute for Employment Research (*IAB*). These restricted public data contain employment histories based on social security records for essentially the universe of workers and establishments in Germany, excluding civil servants and the self-employed.

The linked employer-employee nature of the data means that we observe all workers within each establishment and that we can track both entities over time.

Firm financials (Amadeus). We make use of firm financials data comprising private and public firms' balance sheet information based on data from *Amadeus*. These private data can be purchased from Bureau van Dijk (BvD) and are distributed as part of the Orbis Historical data product. The merge between the IAB linked employer-employee data and the Amadeus firm financials data forms part of the IAB-internal data product *Orbis-ADIAB* (Schild, 2016; Antoni et al., 2018).[20] This merge allows us to link individual establishments in the IAB data at the firm level.

Board compensation (BoardEx). We supplement the IAB worker earnings records with small-sample information on compensation—including salary and bonus components—of board members at companies listed on the German stock market index (DAX) from 2010 to 2016. We source this information from *BoardEx*, which we access via Wharton Research Data Services (WRDS) and merge with the other datasets via consistent BvD identifiers.

Bank-firm relationships (Creditreform). To capture firms' bank credit relationships, we primarily use firms' self-reported bank relationships collected by *Creditreform*. These data identify private and public firms' principal and other bank affiliations, which we merge as before using BvD identifiers.

Loan transactions (DealScan). As an additional source of information on firms' bank credit relationships, we use data from Thomson Reuters *DealScan* on (typically large, public) firms' transactions in the syndicated loans market based on public filings, company statements, and media reports. We hand-match data from DealScan to firms in the other datasets using a combination of firm name, industry, and address, similar to Acharya et al. (2019) and Heider et al. (2019).

Bank balance sheets (SNL Financial). To measure banks' exposure to negative rates, we take balance sheet data from *SNL Financial* (now named S&P Global Market Intelligence), a financial news and data services provider, for all banks that appear in the other datasets.

[20] At the time of writing, this data product is available to employees of IAB and will be made available to the global research community along with other IAB data products in the future.

4.2 Description of Variables

The main variables of interest for our analysis are the deposit ratios of firms' relationship banks as well as workers' wages and employment status. We measure a firm's exposure to negative rates through the mean ratio of deposits to assets across all euro-area (typically German) banks that a firm reports to be in a banking relationship with during the preperiod from 2010 to 2013. Wages are defined as the mean (log) daily earnings of full-time employees as reported in the IAB linked employer-employee data.[21] Since these data are based on social security records and subject to statutory contribution limits, earnings are winsorized around the 90$^{\text{th}}$ percentile of the population. Finally, unemployment is defined as a worker leaving our sample of employment records in a given year, excluding temporary leaves and recalls.

4.3 Sample Selection

We use data from years 2010 to 2017 to maximize our sample period subject to a balanced number of years before and after the introduction of negative monetary policy rates in 2014. Exploiting the matched employer-employee dimension of the merged data, we build a panel of workers indexed by i across firms indexed by j and years indexed by t. Within a given worker-year it, we keep the main job j, which we define as the highest-paid full-time job held by worker i in year t. We then limit the sample to firms with information on bank relationships from Creditreform, which we use to construct the credit supply shock exposure variable $\mathit{Credit}_{jt} \equiv \mathit{Deposit\ ratio}_j \times \mathit{After}(2014)_t$ as part of our empirical strategy.

4.4 Summary Statistics

Our final sample covers approximately 36% of total full-time workers in Germany, thus constituting a large sample of the German labor force. Table 1 presents summary statistics for this sample and key variables from the merged dataset. In Panel A, we start out with German firms' activities in the syndicated loans market. As will be the case in Table 3, we build a panel at the firm-bank-half-year level for syndicated loans granted to German firms in DealScan. Interestingly, the average $\mathit{Deposit\ ratio}_j$ in this dataset is lower than in the merged administrative linked employer-employee data (see Panel C), as only relatively large (typically publicly listed) firms in Germany access the syndicated loans market. Large firms are, in turn, more likely to contract with banks

[21] We separately study part-time versus full-time employment shares as an outcome in our firm-level analysis.

that rely less on deposit funding (and more on market funding), e.g., investment banks.

Panel B shows summary statistics at the worker-year level based on the merged data. Altogether, our sample covers over 72 million worker-year observations, or an average of 9 million observations per year. The average worker earns 37,294 euros (around 44,000 US dollars) per year, with a standard deviation of 18,541 euros (around 22,000 US dollars). Approximately 9.6 percent of observations in a balanced panel based on our data are classified as unemployment spells.

Finally, Panel C summarizes key variables at the firm-year level based on the merged data. The average deposit ratio is around 0.654. The mean P90/P10 wage percentile ratio is around 4.360 for all firms and around 2.581 for the subset of publicly listed firms. Using small-sample evidence on compensation of board members at public firms, we find a large pay gap between board members and regular workers. While the average firm in our sample has 3,935 employees, the firm size distribution is positively skewed and fat-tailed. The mean number of nonmanagerial employees is 3,777, while the mean number of part-time employees stands at 1,993.

Table 2 presents firm-level summary statistics separately for firms in the top and bottom quartiles of the distribution of deposit ratios. Firms in relationships with high-deposit banks (Panel A), which have greater exposure to negative rates, and firms in relationships with low-deposit banks (Panel B) are similar along several observable characteristics, including their average wage and worker composition in terms of gender, nationality, and university education.

There are, however, some notable differences between the two groups. Although mean employment is similar across groups, the median firm in relationships with high-deposit banks has nine employees, compared to twelve employees at firms in relationships with low-deposit banks. Similarly, while the average firm in relationships with high-deposit banks has an asset value of 3.4 million euros, the average asset value of firms in relationships with low-deposit banks is 31.6 million euros. Note, however, that this difference is relatively smaller when comparing median asset values of 0.73 million versus 1.17 million euros.

In terms of the remaining variables, both groups appear relatively similar. For example, leverage, defined as the ratio of the sum of long-term debt and short-term loans to assets, returns on assets (ROA), ROA volatility, defined as the six-year standard deviation of a given firm's ROA using profits and losses before taxes, as well as cash- and investment-to-asset ratios are virtually identical across groups.

It is important to note that baseline differences between firms in relationships with high- versus low-deposit banks are not a threat to our identification. By including firm fixed effects in all worker-level regression specifications, we control for permanent (unobserved) firm heterogeneity. We also explicitly address nonrandom matching between firms and banks by including bank-firm match fixed effects in all credit-related specifications. In our analysis of within-firm inequality, we also include firm-year fixed effects, which account for permanent as well as time-varying (unobserved) employer differences.

5 Results

We present our results in two steps. In the first step, we study the firm-level credit supply shock due to the introduction of negative monetary policy rates. In the second step, we quantify the effect of German firms' exposure to negative rates through their banking relationships on the distribution of wages and employment.

5.1 Effect of Negative Monetary Policy Rates on Credit Supply

The goal of this section is to estimate the extent to which German firms in relationships with high-deposit, rather than low-deposit, banks see a relative reduction in credit supply following the introduction of negative monetary policy rates in June 2014. To conform as closely as possible with the Orbis-ADIAB sample, we limit our analysis to German firms in Amadeus with data coverage throughout 2010–2017 and at least ten employees. Furthermore, we drop a very small number of firms that, according to the Amadeus data, have ratios of the sum of long-term debt and short-term loans over assets of 0.05 and less, as those firms are unlikely to be affected by any financing shock.

We start by using transaction-level data on syndicated loans of German firms based on DealScan. While only a subset of German firms in our sample are active in the syndicated loans market, the granularity of these data allows us to control for a rich set of codeterminants of firms' credit access.

We focus on banks that act as lead arrangers in the syndication process. Lead arrangers are those members of a syndicate that are typically responsible for traditional bank duties including due diligence, payment management, and monitoring of the loan (Ivashina and Scharfstein, 2010). Based on all lead banks' shares of completed syndicated loans of German corporations between January 1, 2010 and December 31, 2017, we extend the sample to a balanced panel of borrowers j and banks k over time t at semi-annual frequency.

To measure a firm's exposure to the introduction of negative monetary policy rates, we first compute the mean deposit ratio in 2013 of its relationship banks in the preperiod from 2010 to 2013, which we denote *Deposit ratio*$_j$. We then estimate the following regression specification at the firm-bank-time level *jkt*, where time therefore refers to the semi-annual level:

$$y_{jkt} = \beta \textit{Deposit ratio}_j \times \textit{After}(06/2014)_t + \kappa_{jk} + \lambda_{kt} + \varepsilon_{jkt}, \tag{19}$$

where y_{jkt} is an outcome associated with lending by bank k to firm j at time t, *Deposit ratio*$_j$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013, $\textit{After}(06/2014)_t$ is an indicator for whether the date falls on or after June 2014, and κ_{jk} and λ_{kt} denote firm-bank and bank-time fixed effects, respectively. Our interest lies in estimates of the coefficient β in equation (19), which we interpret as the effect of greater exposure to negative rates on outcome y_{jkt}. We cluster standard errors at the bank level.

Table 3 presents the results of estimating (19). In the first two columns, the dependent variable is an indicator for any non-zero share of firm j's syndicated loans retained by bank k in t. In the first column, we include only bank-firm and time fixed effects, and find that a one standard deviation increase in *Deposit ratio*$_j$ (see Panel A in Table 1) is associated with a $0.126 \times 0.084 = 1.1$ percentage points lower likelihood of attaining any loan. The mean level of *Deposit ratio*$_j$ is 0.374, which implies that the average effect is a reduction in said likelihood by 3.1 percentage points.

This estimate becomes even larger in the second column, which adds bank-time fixed effects to control for bank-wide shocks such as regulatory changes that affect bank lending across all clients. In this case, the coefficient of interest, β, is estimated off firms in relationships with the same bank in a given year. Among these firms, β captures the effect of differential exposure to high- versus low-deposit banks in the preperiod on current lending by preexisting or new bank relationships.

All of these results hold when we replace the dependent variable by the natural logarithm of one plus the total loan volume granted to firm j by bank k in t, as shown in the last two columns. For each syndicated loan, we use information on each lead bank's share from DealScan, which we use to compute each lead bank's total loan amount granted to a firm in a given time period.[22]

Together, these findings imply that firms in relationships with high-deposit banks receive less credit following the introduction of negative policy rates.

[22]Whenever available, we use loan shares as reported in DealScan. Otherwise, similar to Chodorow-Reich (2014), we set the total loan share retained by lead arrangers in the syndicate equal to the sample mean, and divide it equally among all lead arrangers in the syndicate.

In the next step, we establish that this reduction in borrowing is due to a reduction in credit supply by banks rather than a reduction in firms' credit demand. Following Heider et al. (2019), we use bank k's deposit ratio as the exposure variable and limit the sample to lead banks in negative-rate currency areas (as opposed to all banks in the database, which we used before) from which firm j borrowed anytime in the preperiod. In doing so, we test for a response in the intensive margin of lending, i.e., whether high-deposit banks reduce credit supply to their existing borrowers following the introduction of negative policy rates.

The results in Table 4 show a significant reduction in credit supply for different time windows around the introduction of negative rates. In the first column, we include firm-time fixed effects that absorb time-varying unobserved heterogeneity at the firm level, including loan demand (Khwaja and Mian, 2008). We find that high-deposit banks reduce their credit supply after the introduction of negative policy rates. Using these estimates, a one standard deviation increase in banks' deposit ratios implies a lower likelihood of granting any loans through syndication by $0.176 \times 0.085 = 1.5$ percentage points.

Our identification rests on the assumption that negative rates are special.[23] To corroborate this assumption, in column 2 we interact the deposit ratio with an indicator for the period starting in July 2012, which is when the ECB reduced the deposit facility rate from 0.25% to 0%, the lowest nonnegative monetary policy rate. We find that high-deposit and low-deposit banks do not respond differently to this cut in positive rates. Instead, we continue to find that high-deposit banks start reducing their credit supply after the introduction of negative policy rates in June 2014. Our interpretation of this finding is that banks' funding structure matters for bank lending only if the passthrough of monetary policy to deposit rates breaks down. This is the case when rates go below zero as banks are reluctant, or unable, to pass on negative rates to their depositors.

In column 3, we estimate the same specification as in column 1 but use a short time window, from 2013 to 2015, around the introduction of negative policy rates in June 2014 so as to reduce the likelihood of other bank-level events, including other concurrent monetary policy decisions, interfering with our identification. The difference-in-differences estimate becomes somewhat larger and is significant at the 5% level. As before, all of these results hold when we replace the dependent variable by the actual loan amounts granted by lead banks through syndication (columns 4 to 6).

Our results imply that high-deposit banks reduce credit supply in response to the introduction

[23] In this sense, our analysis is similar to that of the reversal interest rate (Brunnermeier and Koby, 2018).

of negative policy rates. As seen in Table 3, firms are unable to compensate for this reduction in credit access by switching to other banks, e.g., those outside negative-rate currency areas. In our model in Section 2, a firm's credit limit can be interpreted as the sum of all sources of external debt financing. To map this into the data, we confirm, using the firm-level panel in Amadeus, that German firms in relationships with high-deposit banks see a reduction in overall debt financing following the introduction of negative rates. To this end, we run the following firm-year-level regression:

$$y_{jt} = \beta Deposit\ ratio_j \times After(2014)_t + \psi_j + \delta_t + \varepsilon_{jt}, \tag{20}$$

where y_{jt} is the dependent variable of interest at the firm-year level, where t represents the respective year-end, $Deposit\ ratio_j$ is the average deposits-to-assets ratio, measured in 2013 across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013, $After(2014)_t$ is a dummy variable for the years 2014–2017, and ψ_j and δ_t denote firm and year fixed effects, respectively. Standard errors are clustered at the firm level.

Figure 2 plots estimates of β from equation (20), using as dependent variable $Leverage_{jt}$, which we define as the ratio of the sum of long-term debt and short-term loans (in Amadeus) to firm j's assets in year-end t. The coefficient is statistically insignificantly different from zero throughout the preperiod 2010–2013, and becomes negative and significant at the 10% level starting with the first full year of negative rates in 2015. In terms of point estimates, a one standard deviation increase in $Deposit\ ratio_j$ (see Panel C in Table 1) translates into a reduction in leverage by up to $0.04 \times 0.153 = 0.6$ percentage points. This shows that firms in relationships with high-deposit banks do not only lose credit from their existing lenders but also wind up with less leverage overall, suggesting that firms can imperfectly substitute credit across financing sources. As a result, firms experience what corresponds to a tightening of their credit constraint ξ_j in our model in Section 2.

In Figure 3, we plot estimates from the same regression, using the natural logarithm of fixed assets (capital) as dependent variable. Interestingly, we find no significant effect on fixed assets, which suggests that the tightening of financial constraints for firms in relationships with high-deposit banks does not lead to notable adjustments in capital following the introduction of negative rates.[24] This finding is consistent with the presence of adjustment costs or irreversibility

[24]We find similar results when looking at either total assets, tangible fixed assets, or intangible fixed assets.

preventing significant movements in capital in response to a credit shock of the observed magnitude, in line with other recent evidence (Ramey and Shapiro, 2001; Cooper and Haltiwanger, 2006; Lanteri, 2018; Winberry, 2020).

As additional evidence for the negative credit supply shock interpretation, Figure 4 shows, using as dependent variable the natural logarithm of total cash and cash equivalents, that firms in relationships with high-deposit banks hoard significantly more cash following the introduction of negative rates. This is in line with theoretical models showing that constrained firms engage in precautionary savings (Almeida et al., 2004). In response to their new financial constraint, firms may adjust their assets (Campello et al., 2011; Berg, 2018), employment (Bacchetta et al., 2019), or average pay (Popov and Rocholl, 2018). As we find no effect on fixed assets, consistent with the presence of capital adjustment costs, we next turn to the adjustments in the distribution of wages and employment.

5.2 Effects on the Distribution of Wages and Employment

So far, we have established that firms in relationships with high-deposit banks experience worse access to credit, not only within preexisting relationships but also across other banks, and to external debt financing more generally. Our next goal is to estimate the effect of firms' exposure to negative policy rates on the distribution of wages and employment in our worker-level data.

Mean effects. We start by looking at effects on mean wages and unemployment, corresponding to specification (14) of our empirical strategy at the worker-year level:

$$y_{ijt} = \beta Deposit\ ratio_j \times After(2014)_t + \theta_{ij} + \zeta_{st} + \varepsilon_{ijt}, \tag{21}$$

where y_{ijt} is an outcome for worker i at firm j in year t, *Deposit ratio*$_j$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013, *After*(2014)$_t$ is a dummy variable for the years 2014–2017, and θ_{ij} and ζ_{st} denote, respectively, worker-firm and state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in.

Table 5 shows results from estimating a variant of equation (21) that uses as dependent variable either worker i's log wage at firm j or her employment status in the following year. When including worker, firm, and year fixed effects, we find that workers at more exposed firms see, on average, a relative reduction in wages (column 1) and higher unemployment risk (column 4). These findings are consistent with the predictions of Lemmas 1 and 3 of our model that a tightening of the credit constraint reduces labor demand, leading firms to cut wages and reduce employment.

Columns 2 and 5 show that the effects on wages and unemployment become stronger when including worker-firm match fixed effects, which means the coefficient of interest, β, is estimated off workers that were either employed at the same firm before and after 2014, or no longer employed only after 2014. Based on these estimates, a one standard deviation increase in firms' exposure, captured by $Deposit\ ratio_j$, translates into $0.153 \times 0.077 = 1.2$ percent lower wages and a $0.153 \times 0.011 = 0.2$ percentage points increase in the probability of becoming unemployed. These estimates are robust to, and become even stronger after, including state-year fixed effects in columns 3 and 6, which control for time-varying unobserved heterogeneity associated with firm j's location.

Within-firm heterogeneity. These estimated mean effects on wages and employment may mask important heterogeneity across worker groups within firms. To investigate this, we estimate the following variant of specification (15) of our empirical strategy, which adds an interaction term indicating a worker's position in the within-firm wage distribution:

$$
\begin{aligned}
y_{ijt} = {} & \beta_1 Deposit\ ratio_j \times After(2014)_t \times Bottom\ 20\%\ within\ firm_i \\
& + \beta_2 Deposit\ ratio_j \times After(2014)_t \times Middle\ 60\%\ within\ firm_i \\
& + \beta_3 Deposit\ ratio_j \times Bottom\ 20\%\ within\ firm_i + \beta_4 Deposit\ ratio_j \times Middle\ 60\%\ within\ firm_i \\
& + \beta_5 After(2014)_t \times Bottom\ 20\%\ within\ firm_i + \beta_6 After(2014)_t \times Middle\ 60\%\ within\ firm_i \\
& + \theta_{ij} + \eta_{jt} + \varepsilon_{ijt}, \qquad (22)
\end{aligned}
$$

where y_{ijt} is either the natural logarithm of the wage or an indicator for unemployment next period for worker i employed at firm j in year t, $Bottom\ 20\%\ within\ firm_i$ ($Middle\ 60\%\ within\ firm_i$) is an indicator variable for whether worker i's wage is in the bottom 20% (middle 60%) of the wage distribution of the firm where worker i was employed in the last available year during the preperiod from 2010 to 2013, and θ_{ij} and η_{jt} denote worker-firm and firm-year fixed effects, respectively. The coefficients of interest in equation (22) are β_1 and β_2, which capture the extent to which firms' exposure to negative rates differentially affects workers within the bottom 20% and middle 60% of the wage distribution relative to workers in the top 20%.

Table 6 presents the results from estimating specification (22) on the data. We always include worker fixed effects, controlling for time-invariant heterogeneity at the worker level. In column 1, we include also firm and year fixed effects, and replace those by firm-year fixed effects in column 2. Firm-year fixed effects control for time-varying heterogeneity at the firm level, e.g., firm-wide developments that may be correlated with firms' heterogenous exposure to negative policy rates through their banking relationships, and as such subsume state-year fixed effects, which we included in columns 3 and 6 of Table 5.

In this manner, we find that individuals that used to earn a wage in the bottom 20% of their respective firms' wage distributions see their wages grow more at more exposed firms after the introduction of negative policy rates than the top 20% (the omitted category). This result remains robust after adding worker-firm fixed effects in column 3. A one standard deviation increase in firms' exposure as captured by *Deposit ratio*$_j$ translates into a $0.153 \times 0.051 = 0.8$ percent reduction in wages of workers in the top 20% versus those in the bottom 20% of the within-firm wage distribution. Since the coefficient of interest for the wage regression is now estimated off workers who stay at the same employer before and after the introduction of negative rates, these results are driven by wage effects on incumbents rather than new hires.

In the last three columns, we estimate specification (22) with the dependent variable replaced by an indicator for whether worker i is unemployed in year $t+1$. We find significant unemployment effects for workers in the middle 60% of the within-firm wage distribution across all three specifications. In column 4 and column 6, when including worker-firm match fixed effects, we find that all workers outside of the top 20% of the within-firm wage distribution face higher risk of being laid off following the negative credit supply shock. Quantitatively, the additional layoff risk for workers below the top 20% of the within-firm wage distribution amounts to between $0.153 \times 0.013 = 0.2$ and $0.153 \times 0.019 = 0.3$ percentage points based on our preferred specification in column 6. Note that the inclusion of worker-firm match fixed effects implies that we identify the effect in column 6 off workers that did not switch to another firm, neither from employment nor through unemployment, after 2014.

The empirical observation that wages are more rigid for lower-paid workers may partly reflect that, coinciding with our postperiod, Germany introduced a federal minimum wage of 8.50 euros on January 1, 2015. To the extent that workers near the bottom of the within-firm wage distribution find themselves at or near this threshold, their wages are downwardly rigid. On the flipside, stronger downward wage rigidity of low-paid workers could also rationalize our finding that these workers are relatively more likely to become unemployed following the credit supply shock. This finding is consistent with larger firms initially paying a relative premium for high-skill workers, which is subsequently reduced due to the negative credit supply shock.

In summary, we find that initially higher-paid workers see relative wage declines, while initially lower-paid workers are more likely to become unemployed. As a consequence and in line with part (a) of Proposition 1, within-firm wage inequality decreases.

Between-firm heterogeneity. While we have shown that the credit supply shock due to negative policy rates led to lower wages on average, we now address the extent to which different firms adjusted wages differentially. To explore this, we estimate the following variant of specification (16) of our empirical strategy, which adds an interaction term indicating a firm's mean wage rank:

$$\begin{aligned} y_{ijt} = &\beta_1 Deposit\ ratio_j \times After(2014)_t \times Firm\ pay\ rank_j \\ &+ \beta_2 Deposit\ ratio_j \times After(2014)_t + \beta_3 After(2014)_t \times Firm\ pay\ rank_j \\ &+ \theta_{ij} + \zeta_{st} + \varepsilon_{ijt}, \end{aligned} \tag{23}$$

where y_{ijt} is either the natural logarithm of the wage or an indicator for unemployment next period for worker i employed at firm j in year t, $Firm\ pay\ rank_j$ is firm j's mean wage rank among all firms in 2013, with 0 being the lowest rank and 1 being the highest rank, and θ_{ij} and ζ_{st} denote, respectively, worker-firm and state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in. The coefficient of interest in equation (23) is β_1, which captures the extent to which initially higher-paying firms respond differentially to the credit supply shock induced by the introduction of negative monetary policy rates.

Table 7 presents the results from estimating variants of specification (23). Column 1, which includes worker, firm, and year fixed effects, shows that initially higher-paying firms respond to the negative credit supply shock with a relative reduction in wages, but the estimated coefficient falls short of being statistically significant at conventional levels. After including worker-firm fixed effects and therefore focusing on incumbent workers in column 2, the coefficient almost triples and becomes significant, suggesting that changes in worker composition may be important. This continues to hold true in column 3 after replacing year fixed effects by more granular state-year fixed effects of the respective firms.

The remaining three columns test for differential unemployment effects across firm pay ranks. To this end, we replace the dependent variable by an indicator for whether a worker will be unemployed next period. Column 4 shows a negative and significant estimate of the interaction coefficient of -0.028 (standard error of 0.009). In our preferred specification with worker-firm and state-year fixed effects in column 6, the coefficient is still negative and statistically significant, but it is insignificant in column 5 when using year fixed effects instead of state-year fixed effects.

Our interpretation of these findings is that higher-paying firms are plausibly less constrained by a binding minimum wage and other wage floors. As a consequence of the plausibly lower wage rigidity at initially higher-paying firms, a tightening of credit supply leads initially higher-paying firms to decrease their pay by more because they can. Since they can reduce their labor cost by lowering wages, these firms are less inclined to lay off workers following the negative credit supply shock.

In summary, we find that initially higher-paying firms administer relative wage cuts while at the same time retaining (weakly) more of their workforce. As a consequence and in line with part (b) of Proposition 1, between-firm wage inequality decreases.

Firm-level aggregation. In our worker-level analysis above, we have studied the effect of a negative credit supply shock on the distribution of wages within and between firms. Throughout this analysis, we have been *holding constant worker composition* by including worker or worker-firm fixed effects. In addition to our worker-level analysis, we are also interested in outcomes aggregated to the firm level, which we now turn to. In doing so, we explicitly take account of changes in worker composition due to hiring and separations.

To this end, we construct measures of within-firm wage inequality for all firms in each year. We then estimate variants of specification (17) of our empirical strategy at the firm-year level:

$$y_{jt} = \beta \mathit{Deposit\ ratio}_j \times \mathit{After}(2014)_t + \psi_j + \zeta_{st} + \varepsilon_{jt}, \tag{24}$$

where y_{jt} is a measure of within-firm pay inequality for firm j in year t, ψ_j denotes firm fixed effects, and ζ_{st} are state-year fixed effects corresponding to state $s = s(j)$ that firm j is located in.

Table 8 presents the results from estimating specification (24) for different inequality measures and different samples in our data. Columns 1–3 take as dependent variable y_{jt} the log P90-P10 wage percentile ratio. All three columns include firm and state-year fixed effects, thereby controlling for time-invariant firm-specific and time-varying regional heterogeneity. Column 1, which includes all firms in our sample, indicates a modest reduction in within-firm wage inequality at more affected firms, with a coefficient estimate of -0.013 (standard error of 0.006). This is consistent with our worker-level finding of relative wage declines among higher pay ranks within firms, as in Table 6.

Motivated by evidence that larger, publicly listed firms may exhibit greater within-firm wage inequality (Mueller et al., 2017), we run the same regression separately for public firms in column 2. In doing so, we find that the reduction in within-firm inequality due to the negative credit shock is even more emphasized for firms in this small subsample.

One advantage of using this subsample is that it comprises firms that are large and covered also in our syndicated loans data from DealScan, which we have used in Tables 3 and 4. Those firms are likely to receive syndicated loans not only from German and other euro-area banks, but also from non-euro area banks whose lending behavior should not be affected by the introduction of a negative interest-rate policy in the euro area. This enables us to conduct a falsification test in column 3 by adding an interaction term between $\textit{After}(2014)_t$ and $\textit{Non-euro deposit ratio}_j \in [0,1]$, which is the average deposit ratio across all non-euro area lead arrangers (and other banks not based in negative-rate currency areas) that firm j received a syndicated loan from in the preperiod from 2010 to 2013. The respective coefficient amounts to only one-quarter of our difference-in-differences estimate, and is statistically insignificant.

While rich in many dimensions, the IAB linked employer-employee data do not allow us to measure top-wage inequality due to the data being winsorized at the social security contribution threshold, which falls around the 90$^{\text{th}}$ percentile of the population earnings distribution. This type of top-coding may be particularly relevant for the pay structure at public firms, which tend to offer high variable compensation to their top management (Bertrand and Schoar, 2003; Gabaix and Landier, 2008). A plausible way for firms to reduce pay at the top of the distribution is through adjusting such variable compensation.

To test for this, we use information on compensation for executive board members of 26 of the DAX-listed firms from BoardEx.[25] In columns 4–6 of Table 8, we provide small-sample evidence that a negative credit supply shock is associated with a reduction of top-to-bottom wage inequality

[25]Since German company board seats are partly allocated to worker representatives and other nonexecutives (Jäger et al., 2020), we drop these from our data. When estimating effects for nonexecutive board members, who typically do not receive substantial variable compensation, we find no significant response in their relative pay—see Table B.1 in Appendix B.1.

within firms. Column 4 shows a point estimate that is large and negative but noisily estimated and barely significant at the 10% level. Splitting board pay further into salary and bonus pay, we find a significant negative reduction in bonus (column 6), but not in salary (column 5). This suggests that firms take into account the availability of credit, with associated future growth prospects, when reducing top-earners' variable compensation due to tighter financial constraints.

We also consider the effects of the negative credit supply shock on firm-level employment. The key difference between this analysis and our previous worker-analysis is that we now take into account both new hires and separations. Table 9 presents the results from estimating specification (24) for different employment counts. All specifications in this table control for firm and state-year fixed effects. Column 1 shows that firms more exposed to negative rates see a significant reduction in overall employment, which is consistent with Lemma 3 of our theoretical model. We estimate a coefficient of -0.021 (standard error of 0.007), suggesting that a one standard deviation increase in firm-level exposure is associated with a $0.153 \times 0.021 = 0.3$ percent reduction in total employment. Column 2 shows that this effect is around 30% larger for nonmanagerial employees. Column 3 shows that, as a result, more exposed firms see significant reduction in their share of nonmanagerial workers. Finally, column 4 shows that the negative credit supply shock is also associated with a reduction of part-time work, suggesting that those workers are more likely to leave employment or else are asked to work extra hours.

6 Conclusion

Using a theory-guided empirical approach, we study the effects of a monetary policy-induced firm-level credit supply shock on the distribution of wages and employment. To this end, we build a unique dataset spanning the complete credit chain from banks' balance sheet composition to individual-level labor market outcomes in Germany. We identify firm-level variation in credit supply by using information on firms' preexisting bank relationships around the time of the introduction of negative monetary policy rates by the ECB in June 2014. We exploit the fact that firms in relationships with more deposit-reliant banks see a relative reduction in credit supply due to negative rates. Credit tightening in turn lowers wages and employment of workers at those firms. These effects are concentrated among distinct worker groups within firms, with initially lower-paid workers more likely to be fired and initially higher-paid workers see relative wage declines. At the same time, wages decline by more at initially high-paying firms. Consequently, wage inequality within and between firms decreases as a result of the reduction in credit.

There are two important takeaways from our work. First, firm credit affects wages as well as employment. This finding is at odds with models of competitive labor markets but consistent with the predictions of models with frictional labor markets. Second, monetary policy-induced credit supply has important distributional consequences in the labor market. Inequality is not traditionally part of central banks' objective function. Nevertheless, a growing literature finds that understanding heterogeneity between workers and firms is key for monetary policy transmission. Our results highlight firm pay heterogeneity as a novel channel through which monetary policy can have important distributional consequences.

These findings point in interesting directions for future work. First, while our analysis focuses exclusively on workers' wages and employment, it seems natural to explore other margins of adjustment in response to variation in credit supply. Such margins include firm investment in new technologies, worker investment in human capital, and more drastic organizational change such as outsourcing. Second, while our focus on a particular episode with negative monetary policy rates allows us to cleanly identify firm-level variation in credit supply, it would be compelling to study other instances of monetary policy, including conventional and unconventional policies. Different policies may be associated with different effects on the real economy, along with different distributional consequences. Third and finally, our empirical strategy focuses on a relatively recent episode, namely the introduction of negative rates in June 2014. This necessarily means that our findings reflect short- to medium-term adjustments to variation in credit supply. Understanding the long-term effects of credit disruptions on worker-level outcomes appears equally important and deserving of future investigation.

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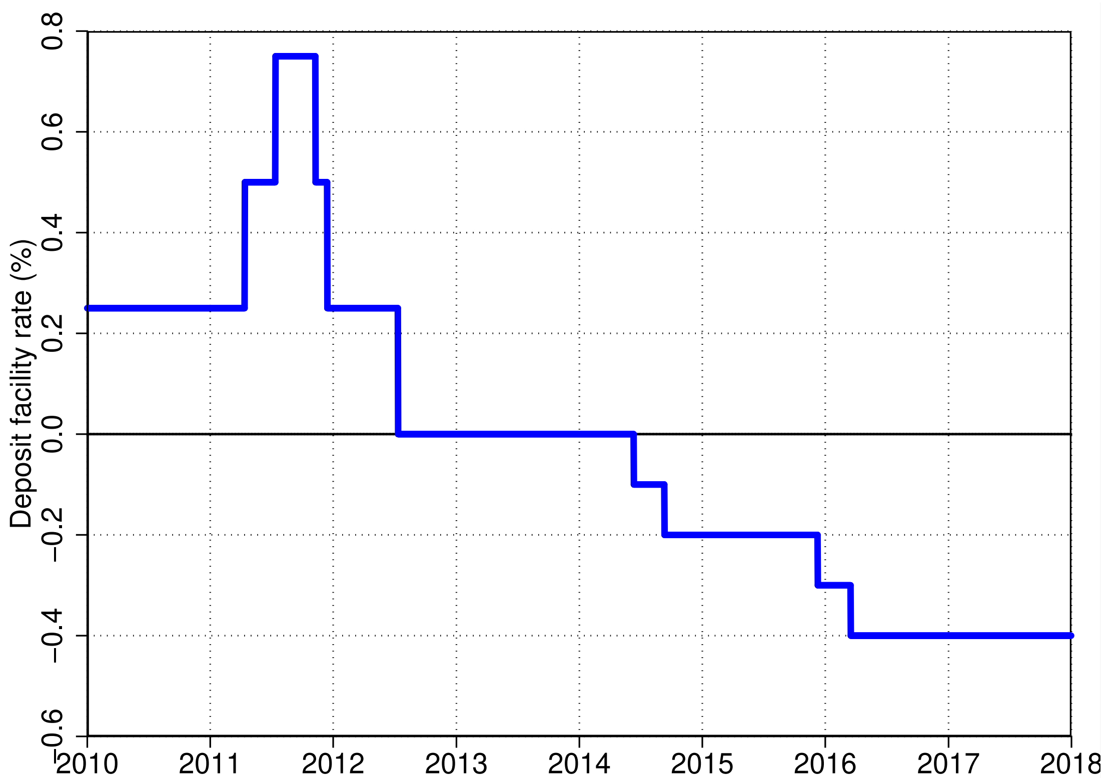
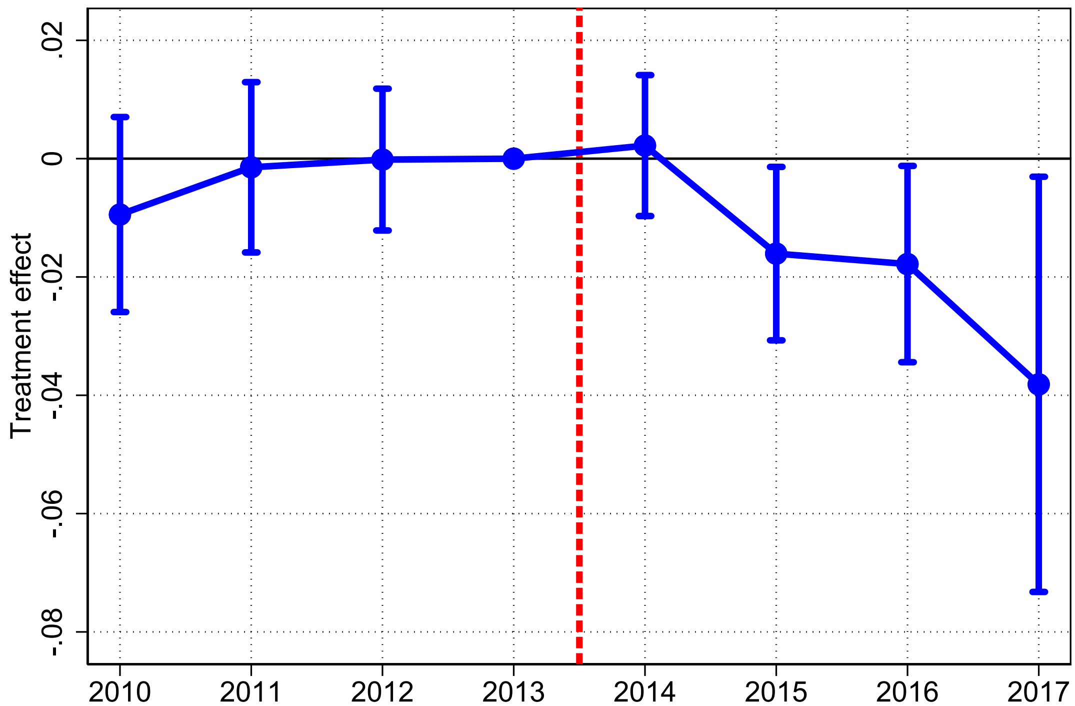
Figures

Figure 1: Deposit Facility Rate by Eurosystem, January 2010 – December 2017



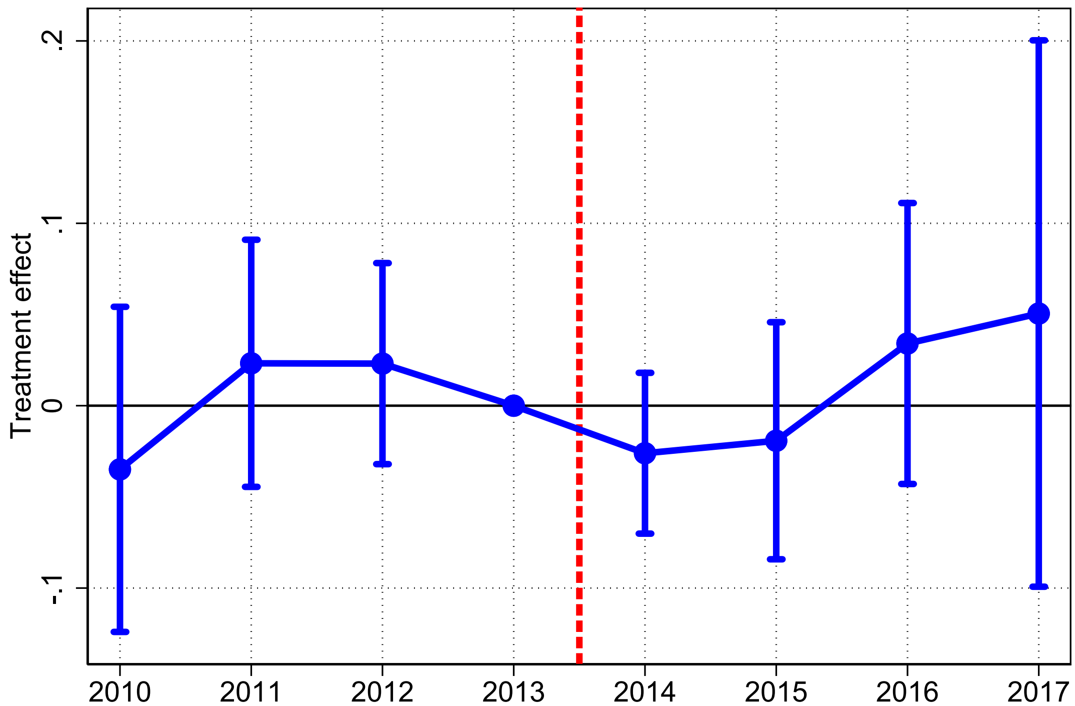
Notes: This figure plots the deposit facility rate on overnight deposits with the Eurosystem set by the European Central Bank between January 1, 2010 and December 31, 2017. *Source:* ECB.

Figure 2: Impact of Negative Policy Rates on Firms' Leverage



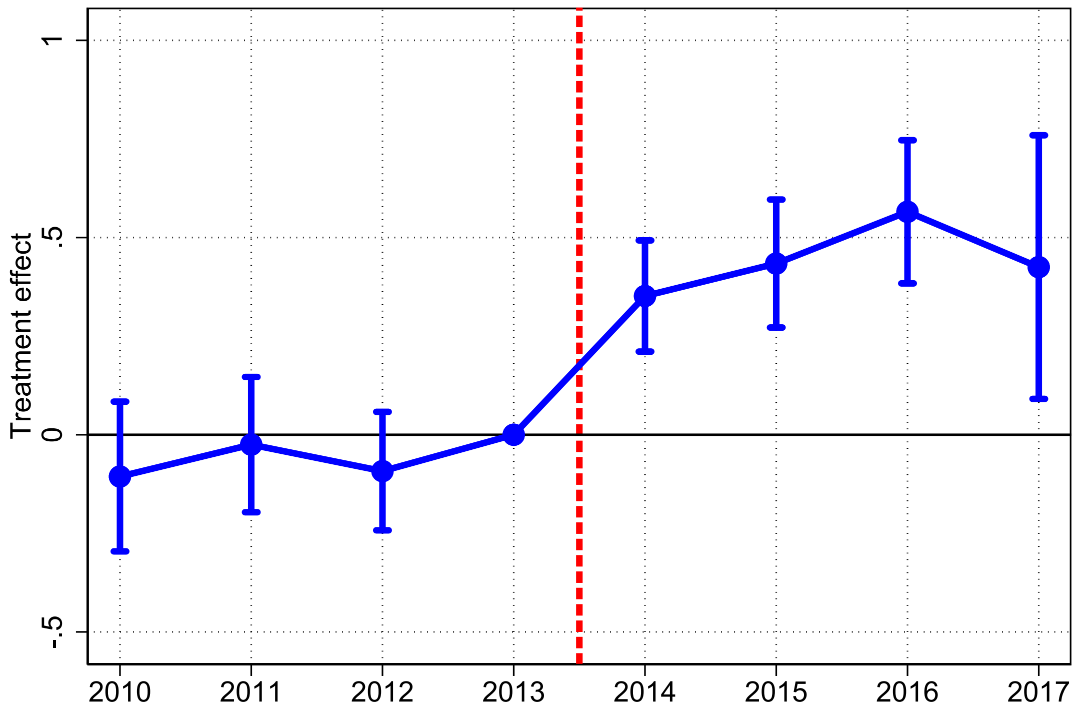
Notes: This figure plots estimates of β, alongside 90% confidence bands, over time (each year represents the respective year-end) based on the difference-in-differences specification in (20), using as dependent variable firm j's leverage ratio, estimated on the sample of German firms in the administrative linked employer-employee data merged with Amadeus from 2010 to 2017.

Figure 3: Impact of Negative Policy Rates on Firms' Fixed Assets



Notes: This figure plots estimates of β, alongside 90% confidence bands, over time (each year represents the respective year-end) based on the difference-in-differences specification in (20), using as dependent variable the natural logarithm of firm j's fixed assets, estimated on the sample of German firms in the administrative linked employer-employee data merged with Amadeus from 2010 to 2017.

Figure 4: Impact of Negative Policy Rates on Firms' Cash Position



Notes: This figure plots estimates of β, alongside 90% confidence bands, over time (each year represents the respective year-end) based on the difference-in-differences specification in (20), using as dependent variable the natural logarithm of firm j's total cash and cash equivalents, estimated on the sample of German firms in the administrative linked employer-employee data merged with Amadeus from 2010 to 2017.

Tables

Table 1: Summary Statistics

Variable	Mean	Std. dev.	P5	P50	P95	No. of observations
Panel A: Firm-bank-half-year level						
Deposit ratio	0.374	0.126	0.235	0.337	0.552	22,016
Any loan share	0.141	0.348	0	0	1	22,016
Total loan amount (bn euros)	0.069	0.194	0.008	0.035	0.152	3,068
Panel B: Worker-year level						
Annualized wage (euros)	37,294	18,541	8,317	35,249	70,949	72,130,131
Unemployed next year	0.096	0.294	0	0	1	66,250,135
Panel C: Firm-year level						
Deposit ratio	0.654	0.153	0.257	0.693	0.837	2,786,063
Wage P90/P10	4.360	212.164	1.000	2.091	9.541	2,751,334
Wage P90/P10 at public firms	2.581	3.222	1.170	2.007	4.352	1,335
Board total P50/Wage P5	180.113	842.094	28.666	60.360	275.762	264
Board salary P50/Wage P5	61.837	293.229	12.932	25.318	85.864	264
Board bonus P50/Wage P5	119.590	571.595	11.868	35.884	193.287	262
No. of employees	3,935	80,052	2	11	142	2,786,063
No. of nonmanagerial employees	3,777	76,843	1	10	133	2,786,063
No. of part-time employees	1,993	40,785	0	3	46	2,786,063

Notes: The summary statistics in Panel A refer to the firm-bank-half-year level for syndicated loans granted to German firms in DealScan, and correspond to the respective descriptions and the sample in Table 3. Total loan amount is conditional on having any loan. The summary statistics in Panel B refer to the dependent variables at the worker-year level, and correspond to the respective descriptions in Tables 5 to 7. The variables in Panel C correspond to the respective descriptions in Tables 8 and 9.

Table 2: Summary Statistics for Firms with High versus Low Exposure to Negative Rates

Variable	Mean	Std. dev.	P5	P50	P95	No. of firms
Panel A: German firms related to banks in the highest quartile of the deposit ratio distribution						
No. of employees	4,459	82,542	1	9	82	88,899
Average annualized wage (euros)	27,361	11,204	11,560	25,800	48,140	88,899
Proportion female	0.252	0.320	0.000	0.111	1.000	88,899
Proportion foreigner	0.070	0.183	0.000	0.000	0.500	88,899
Proportion university	0.110	0.236	0.000	0.000	0.700	88,899
Assets (mm euros)	3.417	65.291	0.079	0.725	8.764	62,117
Leverage	0.201	0.244	0.000	0.098	0.730	34,224
ROA	0.113	0.127	0.005	0.071	0.368	8,191
ROA volatility	0.062	0.064	0.006	0.041	0.188	4,379
Cash/Assets	0.192	0.207	0.001	0.117	0.635	59,711
Investment/Assets	0.070	0.101	0.000	0.033	0.272	25,585
Panel B: German firms related to banks in the lowest quartile of the deposit ratio distribution						
No. of employees	4,235	81,005	1	12	231	87,150
Average annualized wage (euros)	32,846	13,895	12,499	31,099	58,226	87,150
Proportion female	0.297	0.317	0.000	0.200	1	87,150
Proportion foreigner	0.080	0.185	0.000	0.000	0.500	87,150
Proportion university	0.191	0.287	0.000	0.035	1	87,150
Assets (mm euros)	31.612	1,529	0.096	1.172	44.720	61,893
Leverage	0.158	0.228	0.000	0.031	0.675	37,468
ROA	0.125	0.131	0.007	0.085	0.388	13,557
ROA volatility	0.071	0.066	0.009	0.052	0.200	9,636
Cash/Assets	0.194	0.214	0.001	0.113	0.650	59,007
Investment/Assets	0.065	0.105	0.000	0.025	0.271	25,173

Notes: This table shows firm-level summary statistics for the last pre-treatment year 2013, namely for German corporations in the top (Panel A) and bottom (Panel B) quartile of the distribution of $\textit{Deposit ratio}_j$, which is the average deposit ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013.

Table 3: Impact of Negative Policy Rates on Lending to German Firms

	Any loan share $\in \{0,1\}$		$\ln(1 + \text{total loan volume})$	
Variable	(1)	(2)	(3)	(4)
Deposit ratio$_j$ $\times$ After(06/2014)	-0.084***	-0.101***	-1.254**	-1.559***
	(0.030)	(0.030)	(0.511)	(0.514)
Bank-firm FE	Y	Y	Y	Y
Time FE	Y	N	Y	N
Bank-time FE	N	Y	N	Y
N	21,274	21,158	21,274	21,158

Notes: Based on all lead banks' shares of completed syndicated loans of German corporations j anytime from January 2010 to December 2017, the sample is extended so as to represent a balanced panel of all borrower-bank pairs at the semi-annual frequency. Time therefore refers to the semi-annual level. All singletons are dropped from the total number of observations N. In the first two columns, the dependent variable is an indicator for any nonzero share of firm j's loans retained by bank k in t. In the last two columns, the dependent variable is the natural logarithm of one plus the total loan volume granted to firm j by bank k in t. *Deposit ratio*$_j \in [0,1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. *After*(06/2014)$_t$ is a dummy variable for the period from June 2014 onwards. Energy and financial-services borrower firms are dropped. Robust standard errors (clustered at the bank level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Impact of Negative Policy Rates on German Firms' Preexisting Banking Relationships

	Any loan share $\in \{0,1\}$			$\ln(1 + \text{total loan volume})$		
Sample	2010–2017		2013–2015	2010–2017		2013–2015
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio$_k$ $\times$ After(06/2014)	-0.085*	-0.122**	-0.158**	-1.475*	-2.099*	-2.630*
	(0.048)	(0.061)	(0.076)	(0.852)	(1.108)	(1.382)
Deposit ratio$_k$ $\times$ After(07/2012)		0.066			1.113	
		(0.089)			(1.611)	
Bank-firm FE	Y	Y	Y	Y	Y	Y
Firm-time FE	Y	Y	Y	Y	Y	Y
N	15,554	15,554	6,508	15,554	15,554	6,508

Notes: Based on all lead banks' shares of completed syndicated loans of German corporations j anytime from January 2010 to June 2014, the sample is extended so as to represent a balanced panel of all borrower-bank pairs at the semi-annual frequency from 2010 to 2017. Time therefore refers to the semi-annual level. Furthermore, the sample is limited to banks in currency areas with negative monetary policy rates (that lend to German firms at any point in the preperiod from January 2010 to June 2014). In columns 3 and 6, the sample runs from the first half of 2013 to the second half of 2015. All singletons are dropped from the total number of observations N. In the first three columns, the dependent variable is an indicator for any nonzero share of firm j's loans retained by bank k in t. In the last three columns, the dependent variable is the natural logarithm of one plus the total loan volume granted to firm j by bank k in t. *Deposit ratio*$_k$ $\in [0,1]$ is bank k's ratio of deposits over total assets in 2013. *After*(06/2014)$_t$ is a dummy variable for the period from June 2014 onwards. *After*(07/2012)$_t$ is a dummy variable for the period from July 2012 onwards. Energy and financial-services borrower firms are dropped. Robust standard errors (clustered at the bank level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: Effects of Monetary Policy-Induced Credit Supply Shock on Wages and Layoff Rates

		ln(wage)			Unemployed next year $\in \{0, 1\}$	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio × After(2014)	-0.019**	-0.077***	-0.083***	0.007**	0.011***	0.013***
	(0.009)	(0.010)	(0.009)	(0.003)	(0.004)	(0.004)
Worker FE	Y	N	N	Y	N	N
Firm FE	Y	N	N	Y	N	N
Worker-firm FE	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
State-year FE	N	N	Y	N	N	Y
N	70,137,681	67,731,621	67,722,380	65,253,153	63,505,552	63,495,556

Notes: The sample consists of full-time employees i at German corporations j in year t from 2010 to 2017. The dependent variable in the first three columns is the natural logarithm of the wage of individual i at firm j in year t. The dependent variable in the last three columns is an indicator variable for whether individual i is unemployed in year $t + 1$. *Deposit ratio*$_j \in [0, 1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. *After*(2014)$_t$ is a dummy variable for the years 2014–2017. State-year fixed effects are based on the modal location (state) of firm j's establishments. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Effects of Monetary Policy-Induced Credit Supply Shock on Wages and Layoff Rates, by Within-Firm Pay Rank

	ln(wage)			Unemployed next year $\in \{0,1\}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio × After(2014) × Bottom 20% within firm	0.034*	0.069***	0.051***	0.009**	0.004	0.013***
	(0.018)	(0.019)	(0.017)	(0.004)	(0.004)	(0.004)
Deposit ratio × After(2014) × Middle 60% within firm	-0.017**	-0.012*	-0.014**	0.018***	0.016***	0.019***
	(0.007)	(0.007)	(0.007)	(0.002)	(0.002)	(0.002)
Deposit ratio × After(2014)	-0.008			-0.008**		
	(0.007)			(0.003)		
Deposit ratio × Bottom 20% within firm	-0.136***	-0.142***		0.004	0.009**	
	(0.021)	(0.018)		(0.004)	(0.004)	
Deposit ratio × Middle 60% within firm	-0.112***	-0.106***		0.001	0.003	
	(0.015)	(0.013)		(0.003)	(0.003)	
After(2014) × Bottom 20% within firm	0.154***	0.141***	0.071***	0.029***	0.032***	0.050***
	(0.013)	(0.013)	(0.011)	(0.002)	(0.002)	(0.003)
After(2014) × Middle 60% within firm	0.010**	0.007	-0.011**	-0.005***	-0.001	0.000
	(0.004)	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)
Worker FE	Y	Y	N	Y	Y	N
Firm FE	Y	N	N	Y	N	N
Worker-firm FE	N	N	Y	N	N	Y
Year FE	Y	N	N	Y	N	N
Firm-year FE	N	Y	Y	N	Y	Y
N	61,987,235	61,519,347	59,839,079	58,204,386	57,773,587	56,308,377

Notes: The sample consists of full-time employees i at German corporations j in year t from 2010 to 2017. The dependent variable in the first three columns is the natural logarithm of the wage of individual i at firm j in year t. The dependent variable in the last three columns is an indicator variable for whether individual i is unemployed in year $t+1$. *Deposit ratio*$_j \in [0,1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. *After*(2014)$_t$ is a dummy variable for the years 2014–2017. *Bottom* 20% (*Middle* 60%) *within firm*$_i$ is an indicator variable for whether worker i's wage is in the bottom 20% (middle 60%) of the wage distribution of the firm where i was employed in the last available year during the preperiod from 2010 to 2013. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Effects of Monetary Policy-Induced Credit Supply Shock on Wages and Layoff Rates, by Firm Pay Rank

	ln(wage)			Unemployed next year $\in \{0, 1\}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio × After(2014) × Firm pay rank	-0.050	-0.137***	-0.113***	-0.028***	-0.009	-0.020**
	(0.037)	(0.031)	(0.029)	(0.009)	(0.010)	(0.010)
Deposit ratio × After(2014)	-0.017	0.060***	0.045**	0.002	-0.017***	-0.010*
	(0.024)	(0.019)	(0.019)	(0.005)	(0.006)	(0.006)
After(2014) × Firm pay rank	-0.034	0.173***	0.177***	-0.033***	-0.065***	-0.066***
	(0.028)	(0.023)	(0.021)	(0.006)	(0.007)	(0.007)
Worker FE	Y	N	N	Y	N	N
Firm FE	Y	N	N	Y	N	N
Worker-firm FE	N	Y	Y	N	Y	Y
Year FE	Y	Y	N	Y	Y	N
State-year FE	N	N	Y	N	N	Y
N	69,627,349	67,372,241	67,363,297	64,700,521	63,076,967	63,067,608

Notes: The sample consists of full-time employees i at German corporations j in year t from 2010 to 2017. The dependent variable in the first three columns is the natural logarithm of the wage of individual i at firm j in year t. The dependent variable in the last three columns is an indicator variable for whether individual i is unemployed in year $t+1$. *Deposit ratio*$_j \in [0, 1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. *After*(2014)$_t$ is a dummy variable for the years 2014–2017. *Firm pay rank*$_j$ is the rank (from $0 =$ lowest to $1 =$ highest) of firm j in terms of its average pay in 2013. State-year fixed effects are based on the modal location (state) of firm j's establishments. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Firm-Level Effects of Monetary Policy-Induced Credit Supply Shock on Within-Firm Inequality

	ln(P90/P10)	ln(P90/P10)	ln(P90/P10)	ln(P50 board total/P5)	ln(P50 board salary/P5)	ln(P50 board bonus/p5)
Sample	All	Public firms	Public firms	DAX firms	DAX firms	DAX firms
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio × After(2014)	-0.013**	-0.318*	-0.438**	-1.080*	-0.899	-1.137*
	(0.006)	(0.174)	(0.208)	(0.588)	(0.543)	(0.629)
Non-euro deposit ratio × After(2014)			-0.107			
			(0.151)			
Firm FE	Y	Y	Y	Y	Y	Y
State-year FE	Y	Y	Y	N	N	N
Year FE	N	N	N	Y	Y	Y
N	2,738,752	1,321	1,141	264	264	262

Notes: The unit of observation is the firm-year level jt. In column 1, the sample consists of all German corporations j in year t from 2010 to 2017. In columns 2 and 3, the sample is limited to all publicly listed German corporations j that are active in the syndicated loans market in year t from 2010 to 2017. In the last three columns, the sample consists of DAX-listed German corporations j in year t from 2010 to 2016 for which we have board-compensation data from BoardEx. In the first three columns, the dependent variable is the delta log of the wage at the 90^{th} versus 10^{th} percentile of firm j's wage distribution in year t. The dependent variable in column 4 is the delta log of the median total compensation, consisting of a salary and a potential bonus, of executive board members at firm j in year t versus the wage at the 5^{th} percentile of firm j's wage distribution in year t. The dependent variable in column 5 is the delta log of the median salary of executive board members at firm j in year t versus the wage at the 5^{th} percentile of firm j's wage distribution in year t. The dependent variable in column 6 is the delta log of the median bonus (conditional on being nonzero) of executive board members at firm j in year t versus the wage at the 5^{th} percentile of firm j's wage distribution in year t. *Deposit ratio*$_j \in [0,1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. *Non-euro deposit ratio*$_j \in [0,1]$ is the average deposits-to-assets ratio, measured in 2013, across all non-euro area banks (and other banks not based in negative-rate currency areas) from which firm j received syndicated loans anytime from 2010 to 2013. *After*$(2014)_t$ is an indicator variable for the years 2014–2017 in the first three columns (2014–2016 in all remaining columns). State-year fixed effects are based on the modal location (state) of firm j's establishments. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: Firm-Level Effects of Monetary Policy-Induced Credit Supply Shock on Employment

Variable	ln(no. of all employees) (1)	ln(no. of nonmanagerial employees) (2)	Share nonmanagerial (3)	Share part-time (4)
Deposit ratio × After(2014)	-0.021***	-0.028***	-0.006***	-0.011***
	(0.007)	(0.007)	(0.001)	(0.001)
Firm FE	Y	Y	Y	Y
State-year FE	Y	Y	Y	Y
N	2,774,289	2,774,289	2,774,289	2,774,289

Notes: The unit of observation is the firm-year level jt. In the first four columns, the sample consists of all German corporations j in year t from 2010 to 2017. The dependent variable in column 1 is the natural logarithm of the total number of employees at firm j in year t. The dependent variable in column 2 is the natural logarithm of the number of nonmanagerial employees at firm j in year t. The dependent variable in column 3 is the ratio, between 0 and 1, of nonmanagerial staff over all employees at firm j in year t. The dependent variable in column 4 is the ratio, between 0 and 1, of part-time staff over all employees at firm j in year t. $Deposit\ ratio_j \in [0, 1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. $After(2014)_t$ is an indicator variable for the years 2014–2017. State-year fixed effects are based on the modal location (state) of firm j's establishments. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Online Appendix—Not for Publication

A Model Appendix

A.1 Equilibrium Definition

Definition 1. *A* stationary search equilibrium *is a set of worker value functions* $\{S_a, W_a\}_a$ *and policy functions* $\{\phi_a\}_a$*; firm value function* Π *and policy functions* $\{w_a, v_a\}_a$*; wage offer distributions* $\{F_a(w)\}_a$*; measures of unemployed workers* $\{u_a\}_a$*, aggregate job searchers* $\{U_a\}_a$*, aggregate vacancies* $\{V_a\}_a$*, and labor market tightnesses* $\{\theta_a\}_a$*; job offer arrival rates* $\{\lambda_a^u, \lambda_a^e$*; and firm sizes* $\{l_a\}_a$ *such that for all a:*

- *Given* $F_a(w)$ *and* $\{\lambda_a^u, \lambda_a^e\}$*, the value functions* S_a *and* W_a *satisfy equations (1) and (2);*
- *Unemployed workers' job acceptance policy follows a threshold rule* ϕ_a *given by equation (3) and employed workers with wage* w *accept any job* w' *such that* $w' > w$*;*
- *Given* $l_a(\cdot)$*, firms' value function* Π *satisfies equation (5);*
- *Firms policy functions* $\{w_a, v_a\}$ *solve the problem in equation (5);*
- *Measures of unemployed workers are given by equation (4), aggregate job searchers* U_a *are given by equation (6), aggregate vacancies* V_a *are given by equation (7), and labor market tightness* θ_a *is given by equation (8).*
- *Given* θ_a*, the job offer arrival rates* $\{\lambda_a^u, \lambda_a^e\}$ *satisfy equation (9);*
- *Given* $F_a(w)$*,* $\{\lambda_a^u, \lambda_a^e\}_a$*, and* V_a*, firm sizes satisfy equation (10);*
- *The offer distribution satisfies* $F_a(w) = \int_j v_a(j)\mathbf{1}[w_a(j) \leq w]\, d\Gamma(j)/V_a$.

A.2 Proofs

A.2.1 Proof of Lemma 1

Proof. The proof follows closely that in Morchio and Moser (2020). We first reformulate the firm's problem. Define $\tilde{p} = p\frac{1+r}{1+(1+\psi)r}$, where ψ is the Lagrange multiplier on a firm's credit constraint, as in equation (13) of the main text. We then proceed in two steps.

Step 1. In the first step, we prove monotonicity of w_a^* in components of $\tilde{p}$. We can rewrite the firm's FOCs as

$$[\partial w_a]: \quad 1 = (\tilde{p} - w_a)\frac{2\lambda_a^e f_a(w_a)}{\delta_a + \lambda_a^G + \lambda_a^e(1 - F_a(w_a))} \tag{25}$$

$$[\partial v_a]: \quad c_a^{v,0}\frac{\partial \tilde{c}^v(v_a)}{\partial v_a} = T_a(\tilde{p} - w_a)\left(\frac{1}{\delta_a + \lambda_a^G + \lambda_a^e(1 - F_a(w_a))}\right)^2, \tag{26}$$

where $T_a = \mu_a[(u_a + s_a^G)\lambda_a^u(\delta_a + \lambda_a^G + \lambda_a^e)]/V_a$. Equation (25) already shows that the optimal wage w_a is independent of the cost of posting vacancies, proving the first statement. Now consider equation (26); because the term on the right-hand side is always positive for $\tilde{p} > \phi_a$, it follows that optimal vacancies $v_a^*(\tilde{p}, c_a^{v,0})$ are always strictly positive.

We now show that the derivative of wages with respect to $\tilde{p}$ is always positive. Define $h_a(\tilde{p}) = F_a(w_a^*(\tilde{p}))$. Thus:

$$
\begin{aligned}
h_a(\tilde{p}) =& \frac{\int_{\tilde{p}' \geq \phi_a}^{\tilde{p}} \overline{v}_a^*(\tilde{p}) \gamma_a(\tilde{p})}{V_a} \, d\,\tilde{p}' && (27)\\
h_a'(\tilde{p}) =& f_a(w_a^*(\tilde{p}))\, w_a^{*\prime}(\tilde{p}) && (28)\\
f_a(w_a^*(\tilde{p})) =& h_a'(\tilde{p}) / w_a^{*\prime}(\tilde{p}), && (29)
\end{aligned}
$$

where $\overline{v}_a^*(\tilde{p}) = \int v_a^*(\tilde{p}, c') \gamma_a^c(c'|\tilde{p})\, dc'$ is the integral of optimal vacancies conditional on $\tilde{p}$ and $\gamma_a^c(c|\tilde{p})$ is the density of vacancy posting costs $c_a^{v,0}$ conditional on $\tilde{p}$, $\gamma_a(\tilde{p})$ is the marginal density of composite productivity $\tilde{p}$ and $\partial w_a^*(\tilde{p})/\partial \tilde{p} = w_a^{*\prime}(\tilde{p})$ is the derivative of equilibrium wage with respect to $\tilde{p}$. Thus, we can rewrite $h_a'(\tilde{p}) = \frac{\overline{v}_a^*(\tilde{p})}{V_a} \gamma(\tilde{p})$ by differentiating equation (27) using Leibniz's integral rule.

Using these identities, we can write $f_a(w_a^*(\tilde{p})) = \frac{\overline{v}_a^*(\tilde{p})}{V_a} \gamma_a(\tilde{p}) \partial \tilde{p} / \partial w_a^*(\tilde{p})$. Thus, we can rewrite equation (25) as

$$
\frac{\partial w_a^*(\tilde{p})}{\partial \tilde{p}} = (\tilde{p} - w_a^*) \frac{2\lambda_a^e}{\delta_a + \lambda_a^G + \lambda_a^e(1 - h_a(\tilde{p}))} \frac{\overline{v}_a^*(\tilde{p})}{V_a} \gamma_a(\tilde{p}). \tag{30}
$$

Because the right-hand side of this expression is always positive for $\tilde{p} > \phi_a$, it follows that $\partial w_a^*(\tilde{p})/\partial \tilde{p} > 0$, thus proving that equilibrium wage is increasing in $\tilde{p}$.

Step 2. That optimal wages w_a^* are strictly increasing in productivity p and strictly increasing (constant) in the Lagrange multiplier on the credit limit ψ follows from the definition of $\tilde{p}$. □

A.2.2 Proof of Lemma 2

Proof. The proof follows closely that in Morchio and Moser (2020). We first reformulate the firm's problem. Define $\tilde{p} = p \frac{1+r}{1+(1+\psi)r}$, where ψ is the Lagrange multiplier on a firm's credit constraint, as in equation (13) of the main text. Expected profits per worker contacted by a firm is

$$
\pi_a(\tilde{p}, w) = h_a(w) J_a(\tilde{p}, w),
$$

where $h_a(w)$ is the acceptance probability and $J_a(\tilde{p}, w)$ is the value of employing a worker to a firm with composite productivity $\tilde{p}$ providing wage w. Under the assumption that firms maximize long-run profits, the value of employing a worker is simply

$$
\begin{aligned}
J_a(\tilde{p}, w) &= \frac{\tilde{p} - w}{\delta_a + \lambda_a^e(1 - F_a(w))} \\
&= \frac{(\tilde{p} - w) \,/\, (\delta_a)}{1 + \kappa_a^e\,(1 - F_a\,(w))},
\end{aligned}
$$

The acceptance probability for a firm offering w is

$$\begin{aligned}
h_a(w) &= \frac{u_a + s_a^e\left(1-u_a\right)G_a\left(w\right)}{u_a + s_a^e\left(1-u_a\right)} \\
&= \frac{\delta_a + s_a^e\left(\lambda_a^u\right)G_a\left(w\right)\left(\delta_a+\lambda_a^u\right)}{\delta_a + s_a^e\left(\lambda_a^u\right)\left(\delta_a+\lambda_a^u\right)} \\
&= \frac{1 + s_a^e\kappa_a^u G_a\left(w\right)\left(1+\kappa_a^u\right)}{1 + s_a^e\kappa_a^u\left(1+\kappa_a^u\right)} \\
&= \frac{1 + s_a^e\kappa_a^u\left[\frac{F_a(w)}{1+\kappa_a^e[1-F_a(w)]}\right]\left(1+\kappa_a^u\right)}{1 + s_a^e\kappa_a^u\left(1+\kappa_a^u\right)} \\
&= \frac{1+\kappa_a^e\left[1-F_a\left(w\right)\right] + s_a^e\kappa_a^u F_a\left(w\right)\left(1+\kappa_a^u\right)\left[1+\kappa_a^e\left[1-F_a\left(w\right)\right]\right]}{\left[1+s_a^e\kappa_a^u\left(1+\kappa_a^u\right)\right]\left[1+\kappa_a^e\left[1-F_a\left(w\right)\right]\right]},
\end{aligned}$$

where $\kappa_a^u = \lambda_a^u/\delta_a$. Combining expressions, expected profits per contacted worker are

$$\begin{aligned}
\pi\left(\tilde{p},w\right) &= h\left(w\right)J\left(\tilde{p},w\right) \\
&= \frac{\left\{1+\kappa_a^e\left[1-F_a\left(w\right)\right] + s_a^e\kappa_a^u F_a\left(w\right)\left(1+\kappa_a^u\right)\left[1+\kappa_a^e\left[1-F_a\left(w\right)\right]\right]\right\}\left(\tilde{p}-w\right)}{\left[1+s_a^e\kappa_a^u\left(1+\kappa_a^u\right)\right]\left[1+\kappa_a^e\left(1-F_a\left(w\right)\right)\right]^2\left(\delta_a\right)}.
\end{aligned} \tag{31}$$

Then the firm's problem becomes

$$\max_{w,v}\left\{\pi_a\left(\tilde{p},w\right)vq_a - c_a\left(v\right)\right\}.$$

Therefore, the optimal wage and vacancy policy functions satisfy

$$\begin{aligned}
w_a^*\left(\tilde{p},\cdot\right) &= \arg\max_w \pi_a\left(\tilde{p},w\right) \\
\frac{\partial c_a\left(v^*\left(\tilde{p},\cdot\right)\right)}{\partial v} &= \max_w \pi_a\left(\tilde{p},w\right).
\end{aligned} \tag{32}$$

Since the vacancy cost function $c\left(\cdot\right)$ is convex, and $\pi\left(\tilde{p},w\right)$ in equation (31) is strictly increasing in $\tilde{p}$, then it follows from an application of the envelope theorem to equation (32) that $v^*\left(\tilde{p},\cdot\right)$ is strictly increasing in $\tilde{p}$. Therefore, $v_a^*(\cdot)$ is strictly increasing in productivity p and strictly increasing (constant) in the Lagrange multiplier on the credit constraint ψ for credit contsrained (unconstrained) firms. □

A.2.3 Proof of Lemma 3

Proof. The proof follows directly by combining Lemmas 1 and 2. □

A.2.4 Proof of Proposition 1

Proof. Consider the impact of a lower credit limit ξ_j for all j. We proceed in two parts.

1. That within-firm inequality falls due to a tightening of the credit constraint is a direct consequence of Lemma 1. The lemma states that wages of high-skill workers, w_{a_H}, are strictly increasing in ξ_j among constrained firms but wages of low-skill workers, w_{a_L}, are invariant to ξ_j. Therefore, a reduction in the credit limit ξ_j for all firms strictly reduces the top-to-bottom wage difference in all constrained firms, while leaving that in unconstrained firms

unchanged.

2. Because all low-skill workers earn wages equal to their outside option, a firm's mean wage depends only on its relative employment of high-skill versus low-skill workers and the wage it offers to high-skill workers. Lemma 1 already establishes that the latter is strictly increasing in the credit ξ_j among constrained firms. The desired result follows immediately when holding fixed worker composition. Under the alternative assumption of fixed job offer arrival rates $\{\lambda_a^u, \lambda_a^e\}$ for both a, worker composition is independent of firms' credit constraints. Note that the firm with the lowest composite productivity $\tilde{p}_j$, which is ranked lowest in the firm ladder, will offer the lowest acceptable wage to both worker types, namely $w_{a_L} = \phi_{a_L}$ and $w_{a_H} = \phi_{a_H}$. This is true before and after the change in credit conditions. And since worker composition does not change by our assumption of fixed job offer arrival rates, the mean wage at the lowest-paying firm is also invariant to credit. Therefore, the top-to-bottom difference in mean wages between firms decreases, and strictly so if at least some firms are credit constrained.

□

B Empirical Appendix

B.1 Additional Tables

Table B.1: Effects of Monetary Policy-Induced Credit Supply Shock on Within-Firm Inequality: Nonexecutive Board Members

	ln(p50 board total/p5)	ln(p50 board salary/p5)	ln(p50 board bonus/p5)
Sample	DAX firms	DAX firms	DAX firms
Variable	(1)	(2)	(3)
Deposit ratio × After(2014)	-0.514	-0.106	-0.295
	(0.632)	(0.672)	(1.450)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
N	264	264	105

Notes: The unit of observation is the firm-year level jt. In column 1, the sample consists of all German corporations j in year t from 2010 to 2017. The sample consists of DAX-listed German corporations j in year t from 2010 to 2016 for which we have board-compensation data from BoardEx. The dependent variable in column 1 is the delta log of the median total compensation of nonexecutive board members at firm j in year t versus the annualized wage at the 5$^{\text{th}}$ percentile of firm j's wage distribution in year t. The dependent variable in column 2 is the delta log of the median salary of nonexecutive board members at firm j in year t versus the annualized wage at the 5$^{\text{th}}$ percentile of firm j's wage distribution in year t. The dependent variable in column 3 is the delta log of the median bonus (conditional on being nonzero) of nonexecutive board members at firm j in year t versus the annualized wage at the 5$^{\text{th}}$ percentile of firm j's wage distribution in year t. $\textit{Deposit ratio}_j \in [0, 1]$ is the average deposits-to-assets ratio, measured in 2013, across all (typically German) banks that firm j reports to be in a banking relationship with anytime from 2010 to 2013. $\textit{After}(2014)_t$ is an indicator variable for the years 2014–2016. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.