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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 negative monetary policy rates in 2014 see 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, with initially lower-paid workers more likely to be fired and initially higher-paid workers more likely to receive wage cuts. At the same time, wages decline by more at initially higher-paying firms. Consequently, wage inequality within and between firms decreases. Our results suggest that monetary policy has important distributional effects in the labor market.

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

JEL Classification: D22, G21, G31, G32, J31

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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 the evolution of within- and between-employer pay differences over time.[2] Yet the fundamental drivers of (changes in) within- and between-employer pay differences remain scarcely understood.

Given the limited ability of worker attributes related to labor *supply* to account for empirical pay dispersion, a natural explanation 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 heterogeneity in labor supply curves, 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 the introduction of negative monetary policy rates by the European Central Bank (ECB) in 2014 as a source of variation in credit supply. We show that firms in preexisting relationships with banks that were more exposed to negative rates see a relative reduction in credit. Lower credit in turn is associated with lower firm-level average wages and employment. 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 more likely to receive wage cuts. At the same time, wages decline by more at initially high-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.

[1] See the literature survey contained in Card et al. (2018).

[2] See 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).

To guide our empirical investigation, we develop a simple equilibrium model of firm credit in a frictional labor market. We extend the seminal framework by Burdett and Mortensen (1998) to include worker heterogeneity in skills and firm heterogeneity in credit constraints. Firms of different productivities debt-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, thereby reducing wage inequality.

Motivated 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 extends Heider et al. (2019), which highlights the transmission of negative rates through banks' funding structure. Their identification revolves around the idea that banks are reluctant, or unable, to pass on negative rates to their depositors. This rationalizes our focus on the introduction of negative rates as a shock to banks' funding cost and associated lending capacity, which manifests itself as a negative credit supply shock for firms in sticky relationships with those banks. Banks with greater reliance on deposit funding experience relatively higher funding costs due to negative rates, which leads to a larger reduction in lending by those banks. Our empirical investigation exploits this variation in two stages.

In the first stage of our empirical investigation, we show that German firms in preexisting relationships with high-deposit banks experience a negative credit supply shock due to the introduction of negative rates. More affected firms see significant reductions in credit, both along the extensive margin—receiving any loan—and along the intensive margin—total 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 banks' financial health during this period. Our findings also suggest that more affected firms reduce their leverage, as they are unable to fully substitute credit by switching banks or accessing debt capital markets.

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 1.2 percent, and a significant increase in layoff risk of up to 0.2 percentage points. These estimates control for worker-firm match-specific heterogeneity and aggregate 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 are more likely to receive wage cuts. 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-specific heterogeneity and aggregate time trends. Our estimates suggest that wages decline more at initially higher-paying firms, with wage cuts at top-ranked firms being up to 14 percent greater than at bottom-ranked firms. Consequently, *between*-firm inequality decreases.

In summary, our empirical analysis yields two novel insights. Our first insight is that a monetary policy-induced firm-level credit supply shock affects wages as well as employment. This finding is hard to reconcile with models featuring competitive labor markets, which predict that workers' wages equal their marginal product regardless of their employer's idiosyncratic credit constraints.[4] Our second insight is that monetary policy, through its effect on credit supply, has important distributional consequences in the labor market. In contrast, traditional models and empirical studies of monetary policy focus on its effect on the level—i.e., the first moment—of output, employment, and prices.[5] Both of these insights are consistent with the labor demand channel of firm pay heterogeneity, which lies at the heart of our simple equilibrium model.

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

[5]See Bernanke et al. (1999), Christiano et al. (2005), Smets and Wouters (2007), or Gertler and Karadi (2011).

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 individuals 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.[6] Our findings contribute to this literature by shedding light on the fundamental drivers of within- and between-firm pay differences. To the extent that Germany has seen an increase in credit supply over the past four decades, our findings suggest that changes in firm-level labor demand could explain part of the rise in wage inequality documented over this period (Dustmann et al., 2009; Card et al., 2013).

The existence of firm pay differences for identical workers poses a challenge to models with competitive labor markets, in which the law of one price holds. To rationalize these differences, a large theoretical literature in the tradition of Burdett and Mortensen (1998) has developed equilibrium models of frictional labor markets, which have inspired empirical work by Manning (2003, 2011), among others.[7] In these frictional models, firm pay differences arise due to heterogeneity in labor demand based on productivity 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). Few papers consider the role of firm credit in determining employment and pay through the labor demand channel in a frictional labor 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 that post (rather than bargain) wages and vacancies, which allows us to study the effect of credit supply on within- and between-firm differences in pay and employment.

The second strand of literature related to our work concerns the empirical observation that employers imperfectly insure workers against idiosyncratic shocks. Guiso et al. (2005) estimate positive pass-through of permanent firm-level productivity shocks to workers in Italy on average,

[6] These include, among others, Italy (Iranzo et al., 2008), the U.K. (Faggio et al., 2010), Germany (Card et al., 2013), Brazil (Alvarez et al., 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; Song et al., 2019).

[7] See Postel-Vinay and Robin (2002), Cahuc et al. (2006), Meghir et al. (2015), Hornstein et al. (2011), Engbom and Moser (2018), Bagger and Lentz (2018), and Heise and Porzio (2019) for recent examples.

and more so to managers. Fagereng et al. (2018) find greater pass-through of productivity shocks to workers with higher wealth. Several other studies have focused on pass-through of shocks to productivity[8] and innovation.[9] A novel aspect of our work is our focus on pass-through of firm-level shocks to credit supply. Our estimates are consistent with previous work in that we find positive wage sensitivity to credit supply and greater sensitivity among higher-ranked workers. In related work, Guiso et al. (2013) document that regional credit market development affects starting wages and wage growth of new hires. Our work complements theirs by demonstrating that *firm*-level shocks to credit supply have differential effects on wages and employment throughout the within- and between-firm distribution.

The third strand of literature related to our work concerns the effects of monetary policy and credit supply on the real economy. A long tradition in macroeconomics has been concerned with the credit channel of monetary policy (Bernanke and Gertler, 1995; Gertler and Kiyotaki, 2010), which posits that monetary policy and financial frictions interact in shaping aggregate output, employment, and prices. Credit supply is a key pillar of this theoretical transmission mechanism, and has proved empirically relevant for several macroeconomic outcomes.[10] Our work highlights a different way in which monetary policy-induced credit supply affects the real economy: the distribution of wages within and between firms. Prior studies have examined 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 clearly important to measure employment outcomes, 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. Our paper is among the first to identify firm credit as a source of wage inequality.[11] A small number of concurrent papers measure the responsiveness of worker-level wages to firm-level credit shocks (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 light on the distributional consequences of monetary policy, which have been the subject of a new generation of empirically-oriented models.[12]

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

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

[10]These include investment (Whited, 1992), total factor productivity (Gilchrist et al., 2013), employment (Chodorow-Reich, 2014), innovation (Huber, 2018), and household demand (Mian et al., 2020).

[11]Previous studies by Romer and Romer (1999), Doepke and Schneider (2006), Rajan (2010), Kumhof et al. (2015), and Coibion et al. (2017) have linked inequality to monetary policy and *household* credit.

[12]See Gornemann et al. (2016), McKay and Reis (2016), Kaplan et al. (2018), Debortoli and Galí (2018), Auclert (2019), Bilbiie (2019), Ravn and Sterk (forthcoming), Acharya et al. (2020), Auclert et al. (2020), and Kekre and Lenel (2020). See also Holm et al. (2020) for evidence on the transmission of monetary policy through the household portfolio channel.

Outline. The rest 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 Credit Supply and Wage Dispersion

The purpose of this simple model is to theoretically link credit supply to the distribution of wages and employment. Motivated by the empirical observation that identical workers receive different pay across firms 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.

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

2.1 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

$$\rho S_a(w) = w + \lambda^e_{a_H} \int\limits_{w' > w} \left[S_{a_H}(w') - S_{a_H}(w) \right] dF_{a_H}(w') + \delta_{a_H} \left[W_{a_H} - S_{a_H}(w) \right], \quad \forall a. \tag{1}$$

The value of an unemployed worker of type a is

$$\rho W_a = b_{a_H} + \lambda^u_{a_H} \int\limits_{w'} \max\left\{ S_{a_H}(w') - W_{a_H}, 0 \right\} dF_{a_H}(w'), \quad \forall a. \tag{2}$$

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:

$$\phi_a = b_a + (\lambda^u_a - \lambda^e_a) \int\limits_{w' \geq \phi_a} \frac{1 - F_a(w')}{\rho + \delta_a + \lambda^e_a \left[1 - F_a(w') \right]} dw', \quad \forall a \tag{3}$$

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

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

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

2.2 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 $c_a(0) = 0$, $\partial c_a(0)/\partial v = 0$, and $\partial c_a(v)/\partial v, \partial^2 c_a(v)/\partial v^2 > 0$ 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 $y(p_j, \{l_a\}_{a\in\{a_L,a_H\}}) = p_j \sum_{a\in\{a_L,a_H\}} a l_a$.

Credit constraint. Firms take up debt $D \in \mathbb{R}_+$ to finance their operating costs before production occurs, as in Christiano et al. (2005). 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

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

2.3 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 equals

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

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

[13] An extension in which capital enters production and must be financed upfront is straightforward and omitted here.

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 the unemployed and the employed, 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 steady-state equation describes firms' employment given wage and vacancy policies (w, v), the offer distribution $F_a(w)$, and market tightness θ_a:

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

2.4 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 due to credit constraints as a function of their total wage bill and recruiting costs. 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, $\psi_j > 0$. Consequently, constrained firms offer lower wages and/or post fewer vacancies 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 $\psi_j = 0$, and $\tilde{p}_j < p_j$ for credit constrained firms with $\psi_j > 0$. Firms facing a tighter credit constraint have lower effective productivity as they face a higher shadow cost of resources.

An argument analogous to that in Burdett and Mortensen (1998) shows that equilibrium wages are strictly increasing in effective productivity $\tilde{p}_j$ and the equilibrium offer distribution $F_a(w)$ is continuous and strictly increasing for $w > \max\{\underline{p}a\,,\,\phi_a\}$. Therefore, firms find themselves ranked on a ladder according to their effective productivity $\tilde{p}_j$, which is an increasing function of their productivity p_j and the tightness of their credit constraint as measured by ψ_j.

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 are 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 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 logically from Lemmas 1 and 2 given the model's job ladder structure, as higher-wage firms poach more and lose fewer workers through job-to-job transitions, and higher-vacancy firms recruit more workers from unemployment and from other firms. While the relative employment effect on high-skill versus low-skill workers is an empirical question, 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).

2.5 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 inequality, measured by the top-to-bottom difference in wages within firms; and

(b) lower between-firm inequality, measured by the top-to-bottom difference in mean wages between firms, holding fixed job offer arrival rates $\{\lambda_a^u, \lambda_a^e\}$ for both a.

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 the credit constraint. For part (b), if in addition worker firm-level composition does not change too much, then also mean wages of firms initially at the top of the distribution decrease by more than those at the bottom.[14]

While these model predictions are intuitive, what the wage and employment effects of credit supply in the labor market are is ultimately an empirical question. In the next section, we test these predictions empirically using an identified credit supply shock together with microdata on worker employment histories and firms' bank credit relationships in Germany.

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.

[14] A sufficient condition for the latter is that job offer arrival rates $\{\lambda_a^u, \lambda_a^e\}$ are fixed, although this is not strictly necessary for the result to obtain.

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. The ideal experiment would involve tracing pay and employment of workers in the labor market following a credit supply shock to a known subset of 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 are interested in individual pay and employment at the level of the worker-firm-year ijt. Our simplest specification will be

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

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 δ_t denote worker-firm and year fixed effects, respectively. 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 year fixed effects, we absorb aggregate trends and business cycle fluctuations that affect all workers equally.

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, 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, among other things, 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:

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

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 δ_t denote worker-firm and year fixed effects, respectively. 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 between-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 take into account changes in worker composition due to separations and hires, which we previously held constant when including worker- or worker-firm match-specific controls. To estimate 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

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 as a shock to credit supply the transmission of negative monetary policy rates to bank lending following the implementation of negative *deposit facility rates* in the euro area. We show that this episode differentially affected credit supply to firms depending on their preexisting bank relationships and banks' balance sheet exposure to negative rates.

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 and usually revised every six weeks.[15] In June 2014, for the first time in the history of the euro, the deposit facility rate turned negative and has remained negative since then. Figure 1 shows the deposit facility rate over our period of study between January 1, 2010 and December 31, 2017.

During normal times with positive rates, a lower deposit facility rate is transmitted similarly to rates that determine banks' funding cost. Classical monetary theory predicts that, during normal times, lower interest rates will incentivize banks to increase lending to firms in pursuit of higher returns (Gertler and Kiyotaki, 2010).

Negative rates are different. Heider et al. (2019) argue that banks are reluctant, or unable, to pass on negative rates to their depositors. Consequently, the spread between the deposit facility rate and client rates decreases and banks that rely more on deposit funding incur higher costs of funding. Using transaction-level data from the market for syndicated loans, Heider et al. (2019) show that euro-area banks with greater reliance on deposit funding reduced lending by relatively more in response to the introduction of negative monetary policy rates in 2014.

Our strategy for identifying firm-level credit supply shocks builds on Heider et al. (2019) in that we exploit banks differential exposure to negative rates starting in 2014. We extend their work in three important dimensions. First, we study private and public firms without the restriction to bank-firm relationships in the syndicated loans market in Germany. This allows us to study a significantly larger fraction of firms and employment, since syndicated loans are almost exclusively accessed by large corporations. Second, we move beyond bank-firm loan-level analysis and aggregate the effects of the negative credit supply shock by studying firm-level leverage. Firm-level aggregation is important because firms may be able to partly offset loan-level shocks by substituting toward other existing loans or by forming new lender relationships. Third, we link variation in credit supply to individual outcomes, including pay and employment, which would not be possible absent worker-level panel data. This third point is crucial since we are interested in the distributional effects of the monetary policy-induced credit supply shock.

[15] 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.

We exploit this credit supply shock as follows. As a firm's exposure to negative rates depends on banks' reliance on deposit funding, we sort firms into those in financing relationships with high-deposit versus low-deposit banks. For this purpose, we combine data on firms' self-reported banking relationships with bank-level balance sheet information. Let $\textit{Deposit ratio}_j$ denote the average deposit ratio, that is the ratio of deposits to assets, across all euro-area (typically German) 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 above identification argument, 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. This has been shown to be the case by Heider et al. (2019) using loan-level data from the syndicated loans market across euro-member countries. We extend this finding to the German context using a larger sample of private and public firms without the restriction to the syndicated loans market.

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 $\textit{RankWithin}_i$ 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 ($\textit{Bottom 20\% within firm}_i$) and the center quintiles ($\textit{Middle 60\% within firm}_i$), leaving the top quintile ($\textit{Top 20\% within firm}_i$) as the omitted category.

In the between-firm specification (16), we replace $\textit{RankBetween}_j$ 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 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 lending 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. 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).[16] 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

[16] 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.

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.

4.2 Description of Variables

The main variables of interest for our analysis are the *deposit ratios* of firms' relationship banks and 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.[17] Since these data are based on social security records and subject to statutory contribution limits, earnings are winsorized around the 90th to 95th percentile of the population. Finally, unemployment is defined as a worker leaving our sample of employment records in a given year.[18]

[17] We separately study part-time versus full-time employment shares as an outcome in our firm-level analysis.
[18] We explicitly account for temporary leaves and recalls by excluding these from our unemployment count.

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 $\textit{Credit}_{jt} \equiv \textit{Deposit ratio}_j \times \textit{After}(2014)_t$ 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 $\textit{Deposit ratio}_j$ 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 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 thousand US dollars) per year, with a standard deviation of 18,541 euros (around 22 thousand US dollars). Around 9.6 percent of observations in a balanced panel based on our data are classified as unemployed.

Finally, Panel C summarizes key variables at the firm-year level based on the merged data. The average deposit ratio is around 0.654, which is higher than that of firms in DealScan (in Panel A). This is because syndicated loans are typically granted to relatively large firms, which are more likely to contract with banks that rely more on market, rather than deposit, funding, e.g., investment banks. 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. Average nonmanagerial employees stands at 3,777 and the average number of part-time employees is 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 in terms of 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, that 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), 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 regression specifications, we control for such compositional differences. In our analysis of within-firm inequality, we additionally include firm-year fixed effects, which account for permanent and time-varying 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:

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

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, $\mathit{After}(06/2014)_t$ is an indicator for whether the date falls 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.[19]

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

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 this manner, we test the intensive margin of lending, i.e., whether high-deposit banks reduce their credit supply following the introduction of negative policy rates to their existing borrowers.

Table 4 presents the results. In the first column, we 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 interfering with our identification. We also include firm-time fixed effects that absorb time-varying unobserved heterogeneity at the firm level, including loan demand. We

[19]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.

find that high-deposit banks reduce their credit supply after the introduction of negative policy rates. The same conclusion applies for the whole sample period from 2010 to 2017 in column 2. 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.

To show that negative rates are special, in column 3, 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 rate cut. Instead, we continue to find that high-deposit, rather than low-deposit, banks start reducing their credit supply after the introduction of negative policy rates in June 2014. Our interpretation of this finding is that the pass-through of monetary policy to deposit rates breaks down when rates go below zero, as banks are reluctant, or unable, to pass on negative rates to their depositors. As before, all of these results hold when we replace the dependent variable by the actual loan amounts granted by lead banks through syndication.

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

As the credit limit in our model in Section 2 could be interpreted as the sum of all sources of a firm's external debt financing, we confirm, using our panel of German firms in Amadeus, that firms in relationships with high-deposit banks see a reduction in overall debt financing. For this purpose, we run the following firm-year-level regression:

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

where $Leverage_{jt}$ is the ratio of the sum of long-term debt and short-term loans (in Amadeus) all over firm j's assets 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 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 over our sample period. 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 (a scaled variable between 0 and 1) by up to $0.04 \times 0.153 = 0.6$ percentage points. This suggests that firms in relationships with high-deposit banks do not only experience impaired credit access but also wind up with less leverage overall.

5.2 Effects on the Distribution of Wages and Employment

Having established that firms in relationships with high-deposit, rather than low-deposit, banks experienced 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 sample.

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

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

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 δ_t denote worker-firm and year fixed effects, respectively.

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 3). These findings are consistent with the predictions of Lemmas 1 and A.2.3 of our model that a tightening of the credit constraint reduces labor demand of affected firms, which respond by lowering their wage and vacancy postings.

Columns 2 and 4 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.

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:

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

where y_{ijt} is either 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, such as firm-wide developments that may be correlated with firms' heterogenous exposure to negative policy rates through their banking relationships.

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.[20] 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 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 (column 6). Note that in this context, the inclusion of worker-firm fixed effects implies that we identify the effect in column 6 off workers that did not switch to another firm (neither from employment nor from unemployment) in the year after the shock, i.e., in 2015.

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, the higher 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. In line with our theoretical model, our interpretation of this finding is that larger firms initially pay a premium for high-skill workers, which a negative credit supply shock reduces.

In summary, we find that initially higher-paid workers receive greater wage cuts, 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.

[20] Note that for workers that do not switch firms, it holds that firm j associated with both *Bottom* 20% *within firm*$_i$ (*Middle* 60% *within firm*$_i$) and the fixed effects η_{jt} are identical. This is automatically the case when we include worker-firm match fixed effects.

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:

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

where y_{ijt} is either 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 δ_t denote worker-firm and year fixed effects, respectively. The coefficient of interest in equation (23) is β_1, which captures the extent to which firms at higher pay ranks differentially respond to exposure to negative rates.

Table 7 presents the results from estimating specification (23). Column 1, which includes only firm and year fixed effects, shows that initially higher-paying firms respond to negative rates with relatively larger wage cuts, with a coefficient estimate of -0.107 (standard error of 0.031). The estimated coefficient goes in the same direction but becomes weaker and statistically insignificant after including worker fixed effects in column 2, suggesting that some of this effect is due to changes in worker composition. Including worker-firm fixed effects in column 3, however, shows that there is a significant effect on incumbent workers, with a coefficient estimate of -0.137 (standard error of 0.031).

The remaining three columns test for differential unemployment effects across firm pay ranks. To this end, we estimate a variant of specification (23) with the dependent variable replaced by an indicator for whether a worker will be unemployed next period. Column 4 shows a negative estimate of the interaction coefficient of -0.012 (standard error of 0.007) that falls short of being statistically significant at conventional levels. The coefficient of interest turns statistically negative and significant, with a point estimate of -0.028 (standard error of 0.009) when including worker fixed effects in column 5. In our preferred specification with worker-firm fixed effects in column 6, the coefficient is still negative but again not statistically significant.

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 give greater 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 greater wage cuts among higher pay ranks within firms, as detailed 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 $After(2014)_t$ and $Non\text{-}euro\ deposit\ ratio_j \in [0, 1]$, 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 90th to 95th 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.[21] 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 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 lends support to the idea that firms respond to tighter financial constraints by reducing top-earners' variable compensation.

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

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

fixed effects. Column 1 shows that firms more exposed to negative rates see a significant reduction in overall employment. 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 convert to full-time positions.

6 Conclusion

Using a theory-guided empirical approach, we study the distributional effects of a monetary policy-induced firm-level credit supply shock on individual wages and employment. To this end, we build a unique dataset spanning the complete credit chain from banks' balance sheet exposure to monetary policy to individual worker-level outcomes in Germany. We identify firm-level variation in credit supply by exploiting information on firms' preexisting bank relationships at the time of the introduction of negative monetary policy rates by the ECB in June 2014. We show that firms in relationships with more deposit-reliant banks see a significant reduction in credit as a consequence of the 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 more likely to receive wage cuts. 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 negative credit supply shock.

There are two important takeaways from our work. First, a monetary policy-induced firm-level credit supply shock affects wages as well as employment. This fact contradicts predictions of models featuring competitive labor markets. Instead, this fact is consistent with the predictions of a simple equilibrium model of firm credit in a frictional labor market. Second, monetary policy, through its effect on credit supply, has important distributional consequences in the labor market. Inequality is not traditionally of direct concern to central bankers. Nevertheless, our findings are valuable in light of a new generation of empirically-oriented models that integrate heterogeneity and market frictions in a monetary policy framework. Our work highlights firm pay heterogeneity as a novel channel through which monetary policy can have important distributional consequences.

Our 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 monetary policy episode that involved negative interest 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 monetary policy interventions 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 policy rates in June 2014. This necessarily means that our findings reflect short-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 further investigation.

References

Abowd, John M., Francis Kramarz, and David N. Margolis, "High Wage Workers and High Wage Firms," *Econometrica*, 1999, *67* (2), 251–333.

Acharya, Sushant, Edouard Challe, and Keshav Dogra, "Optimal Monetary Policy According to HANK," *Working Paper*, 2020.

Acharya, Viral V., Tim Eisert, Christian Eufinger, and Christian W. Hirsch, "Whatever It Takes: The Real Effects of Unconventional Monetary Policy," *Review of Financial Studies*, 2019, *32* (9), 3366–3411.

Adamopoulou, Effrosyni, Marta De Philippis, Enrico Sette, and Eliana Viviano, "The Long Run Earnings Effects of a Credit Market Disruption," *Working Paper*, 2020.

Aghion, Philippe, Antonin Bergeaud, Richard Blundell, and Rachel Griffith, "The Innovation Premium to Soft Skills in Low-Skilled Occupations," *Working Paper*, 2019.

Alvarez, Jorge, Felipe Benguria, Niklas Engbom, and Christian Moser, "Firms and the Decline of Earnings Inequality in Brazil," *American Economic Journal: Macroeconomics*, 2018, *10* (1), 149–189.

Antoni, Manfred, Katharina Koller, Marie-Christine Laible, and Florian Zimmermann, "Orbis-ADIAB: From Record Linkage Key to Research Dataset," *FDZ Methodenreport*, 2018.

Auclert, Adrien, "Monetary Policy and the Redistribution Channel," *American Economic Review*, 2019, *109* (6), 2333–67.

_ **, Matthew Rognlie, and Ludwig Straub**, "Micro Jumps, Macro Humps: Monetary Policy and Business Cycles in an Estimated HANK Model," *Working Paper*, 2020.

Babina, Tania, Wenting Ma, Christian Moser, Paige Ouimet, and Rebecca Zarutskie, "Pay, Employment, and Dynamics of Young Firms," *Working Paper*, 2019.

Bagger, Jesper and Rasmus Lentz, "An Empirical Model of Wage Dispersion with Sorting," *Review of Economic Studies*, 2018, *86* (1), 153–190.

Barbosa, Luciana, Andrada Bilan, and Claire Célérier, "Capital Inflows and Skill (Mis)allocation," *Working Paper*, 2020.

Barth, Erling, Alex Bryson, James C. Davis, and Richard Freeman, "It's Where You Work: Increases in the Dispersion of Earnings across Establishments and Individuals in the United States," *Journal of Labor Economics*, 2016, *34* (S2), S67–S97.

Berger, David, Kyle Herkenhoff, and Simon Mongey, "Labor Market Power," *Working Paper*, 2019.

Bernanke, Ben S. and Mark Gertler, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 1995, *9* (4), 27–48.

_ , _ , and Simon Gilchrist, "The Financial Accelerator in a Quantitative Business Cycle Framework," in J. B. Taylor and M. Woodford, eds., *Handbook of Macroeconomics*, Vol. 1 of *Handbook of Macroeconomics*, Elsevier, 1999, chapter 21, pp. 1341–1393.

Berton, Fabio, Sauro Mocetti, Andrea F. Presbitero, and Matteo Richiardi, "Banks, Firms, and Jobs," *Review of Financial Studies*, 2018, *31* (6), 2113–2156.

Bertrand, Marianne and Antoinette Schoar, "Managing with Style: The Effect of Managers on Firm Policies," *Quarterly Journal of Economics*, 2003, *118* (4), 1169–1208.

Bilbiie, Florin O., "Monetary Policy and Heterogeneity: An Analytical Framework," *Working Paper*, 2019.

Burdett, Kenneth and Dale T. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, 1998, *39* (2), 257–273.

Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin, "Wage Bargaining with On-the-Job Search: Theory and Evidence," *Econometrica*, 2006, *74* (2), 323–364.

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *Quarterly Journal of Economics*, 2016, *131* (2), 633–686.

_ , _ , Jörg Heining, and Patrick Kline, "Firms and Labor Market Inequality: Evidence and Some Theory," *Journal of Labor Economics*, 2018, *36* (S1), S13–S70.

_ , Jörg Heining, and Patrick Kline, "Workplace Heterogeneity and the Rise of West German Wage Inequality," *Quarterly Journal of Economics*, 2013, *128* (3), 967–1015.

Chan, Mons, Sergio Salgado, and Ming Xu, "Heterogeneous Passthrough from TFP to Wages," *Working Paper*, 2020.

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis," *Quarterly Journal of Economics*, 2014, *129* (1), 1–59.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," *Journal of Political Economy*, 2005, *113* (1), 1–45.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia, "Innocent Bystanders? Monetary Policy and Inequality," *Journal of Monetary Economics*, 2017, *88*, 70–89.

Debortoli, Davide and Jordi Galí, "Monetary Policy with Heterogeneous Agents: Insights from TANK Models," *Working Paper*, 2018.

Diamond, Peter A., "A Model of Price Adjustment," *Journal of Economic Theory*, 1971, *3* (2), 156–168.

Dickens, William T. and Lawrence F. Katz, "Inter-Industry Wage Differences and Theories of Wage Determination," *NBER Working Paper No. 2271*, 1987.

Doepke, Matthias and Martin Schneider, "Inflation and the Redistribution of Nominal Wealth," *Journal of Political Economy*, 2006, *114* (6), 1069–1097.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg, "Revisiting the German Wage Structure," *Quarterly Journal of Economics*, 2009, *124* (2), 843–881.

Engbom, Niklas and Christian Moser, "Earnings Inequality and the Minimum Wage: Evidence from Brazil," *Federal Reserve Bank of Minneapolis OIGI Working Paper 7*, 2018.

_ and _ , "Firm Pay Dynamics," *Working Paper*, 2020.

Fagereng, Andreas, Luigi Guiso, and Luigi Pistaferri, "Portfolio Choices, Firm Shocks and Uninsurable Wage Risk," *Review of Economic Studies*, 2018, *85* (1), 396–436.

Faggio, Giulia, Kjell G. Salvanes, and John Van Reenen, "The Evolution of Inequality in Productivity and Wages: Panel Data Evidence," *Industrial and Corporate Change*, 2010, *19* (6), 1919–1951.

Fonseca, Julia and Bernardus Van Doornik, "Financial Development, Labor Markets, and Aggregate Productivity: Evidence from Brazil," *Working Paper*, 2019.

Frías, Judith A., David S. Kaplan, Eric Verhoogen, and David Alfaro-Serrano, "Exports and Wage Premia: Evidence from Mexican Employer-Employee Data," *Working Paper*, 2018.

Friedrich, Benjamin, Lisa Laun, Costas Meghir, and Luigi Pistaferri, "Earnings Dynamics and Firm-level Shocks," *NBER Working Paper No. 25786*, 2019.

Gabaix, Xavier and Augustin Landier, "Why has CEO Pay Increased So Much?," *Quarterly Journal of Economics*, 02 2008, *123* (1), 49–100.

Gertler, Mark and Nobuhiro Kiyotaki, "Financial Intermediation and Credit Policy in Business Cycle Analysis," in Benjamin M. Friedman and Michael Woodford, eds., *Handbook of Monetary Economics*, Vol. 3, Elsevier, 2010, chapter 11, pp. 547–599.

_ and Peter Karadi, "A Model of Unconventional Monetary Policy," *Journal of Monetary Economics*, 2011, *58* (1), 17–34.

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek, "Misallocation and Financial Market Frictions: Some Direct Evidence from the Dispersion in Borrowing Costs," *Review of Economic Dynamics*, 2013, *16* (1), 159–176. Special issue: Misallocation and Productivity.

Gornemann, Nils, Keith Kuester, and Makoto Nakajima, "Doves for the Rich, Hawks for the Poor? Distributional Consequences of Monetary Policy," *Working Paper*, 2016.

Guiso, Luigi, Luigi Pistaferri, and Fabiano Schivardi, "Insurance within the Firm," *Journal of Political Economy*, 2005, *113* (5), 1054–1087.

_ , _ , and _ , "Credit within the Firm," *Review of Economic Studies*, 2013, *80* (1), 211–247.

Hagedorn, Marcus and Iourii Manovskii, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies Revisited," *American Economic Review*, 2008, *98* (4), 1692–1706.

_ , Fatih Karahan, Iourii Manovskii, and Kurt Mitman, "Unemployment Benefits and Unemployment in the Great Recession: The Role of Equilibrium Effects," *Working Paper*, 2019.

Håkanson, Christina, Erik Lindqvist, and Jonas Vlachos, "Firms and Skills: The Evolution of Worker Sorting," *Journal of Human Resources*, forthcoming.

Heider, Florian, Farzad Saidi, and Glenn Schepens, "Life below Zero: Bank Lending under Negative Policy Rates," *Review of Financial Studies*, 2019, *32* (10), 3728–3761.

Heise, Sebastian and Tommaso Porzio, "Spatial Wage Gaps in Frictional Labor Markets," *Working Paper*, 2019.

Hershbein, Brad, Claudia Macaluso, and Chen Yeh, "Monopsony in the U.S. Labor Market," *Working Paper*, 2020.

Holm, Martin Blomhoff, Pascal Paul, and Andreas Tischbirek, "The Transmission of Monetary Policy under the Microscope," *Working Paper*, 2020.

Hornstein, Andreas, Per Krusell, and Giovanni L. Violante, "Frictional Wage Dispersion in Search Models: A Quantitative Assessment," *American Economic Review*, 2011, *101* (7), 2873–2898.

Howell, Sabrina and J. David Brown, "Do Cash Windfalls Affect Wages? Evidence from R&D Grants to Small Firms," *Working Paper*, 2020.

Huber, Kilian, "Disentangling the Effects of a Banking Crisis: Evidence from German Firms and Counties," *American Economic Review*, 2018, *108* (3), 868–98.

Iranzo, Susana, Fabiano Schivardi, and Elisa Tosetti, "Skill Dispersion and Firm Productivity: An Analysis with Employer Employee Matched Data," *Journal of Labor Economics*, 2008, *26* (2), 247–285.

Ivashina, Victoria and David S. Scharfstein, "Loan Syndication and Credit Cycles," *American Economic Review: Papers and Proceedings*, 2010, *100* (2), 1–8.

Jäger, Simon, Benjamin Schoefer, Samuel Young, and Josef Zweimüller, "Wages and the Value of Nonemployment," *Quarterly Journal of Economics*, forthcoming.

Jermann, Urban and Vincenzo Quadrini, "Macroeconomic Effects of Financial Shocks," *American*

Economic Review, 2012, *102* (1), 238–271.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, "Macroprudential Policy, Countercyclical Bank Capital Buffers, and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments," *Journal of Political Economy*, 2017, *125* (6), 2126–2177.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante, "Monetary Policy According to HANK," *American Economic Review*, 2018, *108* (3), 697–743.

Kehoe, Patrick J., Pierlauro Lopez, Virgiliu Midrigan, and Elena Pastorino, "On the Importance of Household versus Firm Credit Frictions in the Great Recession," *Working Paper*, 2020.

__, Virgiliu Midrigan, and Elena Pastorino, "Debt Constraints and Employment," *Journal of Political Economy*, 2019, *127* (4), 1926–1991.

Kekre, Rohan and Moritz Lenel, "Monetary Policy, Redistribution, and Risk Premia," *Working Paper*, 2020.

Kiyotaki, Nobuhiro and John Moore, "Liquidity, Business Cycles, and Monetary Policy," *Journal of Political Economy*, 2019, *127* (6), 2926–2966.

Kline, Patrick, Neviana Petkova, Heidi Williams, and Owen Zidar, "Who Profits from Patents? Rent-Sharing at Innovative Firms," *Quarterly Journal of Economics*, 2019, *134* (3), 1343–1404.

Kogan, Leonid, Dimitris Papanikolaou, Lawrence D. W. Schmidt, and Jae Song, "Technological Innovation and Labor Income Risk," *Working Paper*, 2020.

Krueger, Alan B. and Lawrence H. Summers, "Efficiency Wages and the Inter-Industry Wage Structure," *Econometrica*, 1988, *56* (2), 259–293.

Kumhof, Michael, Romain Rancière, and Pablo Winant, "Inequality, Leverage, and Crises," *American Economic Review*, 2015, *105* (3), 1217–1245.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler, "Imperfect Competition, Compensating Differentials and Rent Sharing in the U.S. Labor Market," *Working Paper*, 2019.

Manning, Alan, *Monopsony in Motion: Imperfect Competition in Labor Markets*, Princeton University Press, 2003.

__, "Imperfect Competition in the Labor Market," in O. Ashenfelter and D. Card, eds., *O. Ashenfelter and D. Card, eds.*, 1 ed., Vol. 4B, Elsevier, 2011, chapter 11, pp. 973–1041.

McKay, Alisdair and Ricardo Reis, "The Role of Automatic Stabilizers in the U.S. Business Cycle," *Econometrica*, 2016, *84* (1), 141–194.

Meghir, Costas, Renata Narita, and Jean-Marc Robin, "Wages and Informality in Developing Countries," *American Economic Review*, 2015, *105* (4), 1509–1546.

Mian, Atif, Amir Sufi, and Emil Verner, "How Does Credit Supply Expansion Affect the Real Economy? The Productive Capacity and Household Demand Channels," *Journal of Finance*, 2020, *75* (2), 949–994.

Moll, Benjamin, "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?," *American Economic Review*, 2014, *104* (10), 3186–3221.

Morchio, Iacopo and Christian Moser, "The Gender Pay Gap: Micro Sources and Macro Consequences," *Working Paper*, 2020.

Mueller, Holger M., Paige P. Ouimet, and Elena Simintzi, "Within-Firm Pay Inequality," *Review of Financial Studies*, 2017, *30* (10), 3605–3635.

Postel-Vinay, Fabien and Jean-Marc Robin, "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 2002, *70* (6), 2295–2350.

Rajan, Raghuram, *Fault Lines: How Hidden Fractures Still Threaten the World Economy*, Princeton University Press, 2010.

Ravn, Morten O. and Vincent Sterk, "Macroeconomic Fluctuations with HANK and SAM: an Analytical Approach," *Journal of the European Economic Association*, forthcoming.

Romer, Christina D. and David Romer, "Monetary Policy and the Well-Being of the Poor," *Economic Review*, 1999, *84* (Q I), 21–49.

Schild, Christopher-Johannes, "Linking "Orbis" Company Data with Establishment Data from the German Federal Employment Agency," *German Record Linkage Center Working Paper No. 2016-02*, 2016.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *American Economic Review*, 2005, *95* (1), 25–49.

Smets, Frank and Rafael Wouters, "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 2007, *97* (3), 586–606.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter, "Firming Up Inequality," *Quarterly Journal of Economics*, 2019, *134* (1), 1–50.

Sorkin, Isaac, "Ranking Firms Using Revealed Preference," *Quarterly Journal of Economics*, 2018, *133* (3), 1331–1393.

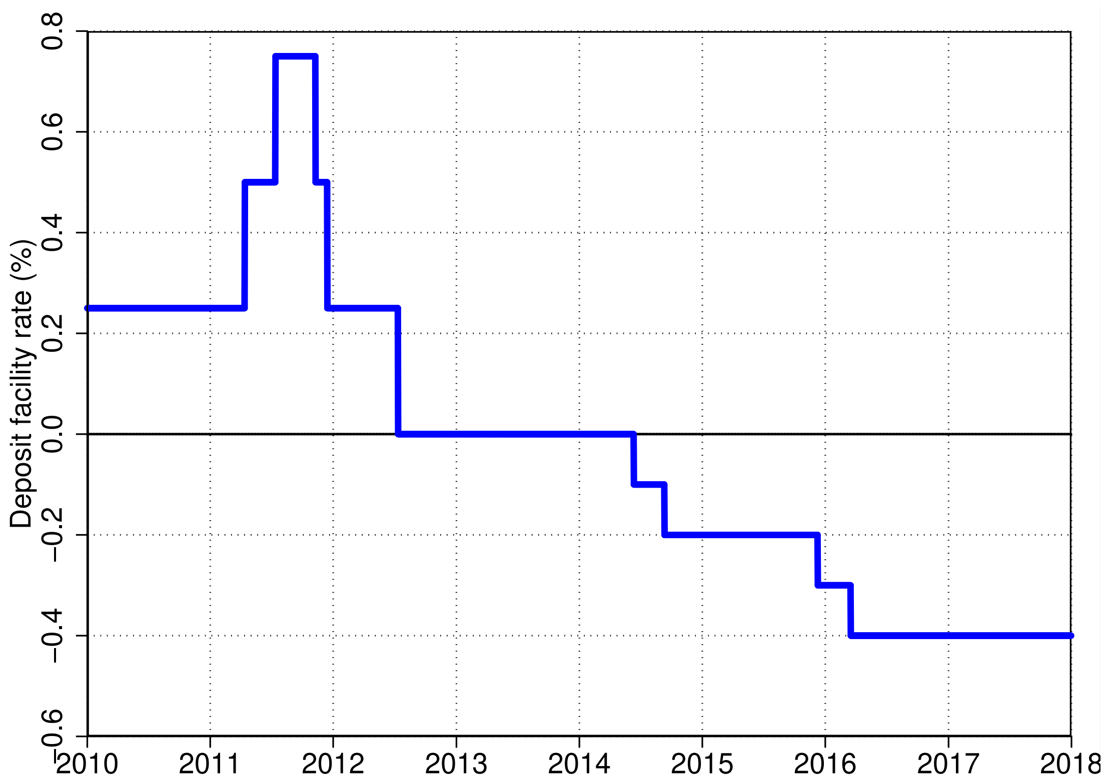
Van Reenen, John, "The Creation and Capture of Rents: Wages and Innovation in a Panel of U. K. Companies," *Quarterly Journal of Economics*, 1996, *111* (1), 195–226.

Wasmer, Etienne and Philippe Weil, "The Macroeconomics of Labor and Credit Market Imperfections," *American Economic Review*, 2004, *94* (4), 944–963.

Whited, Toni M., "Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data," *Journal of Finance*, 1992, *47* (4), 1425–1460.

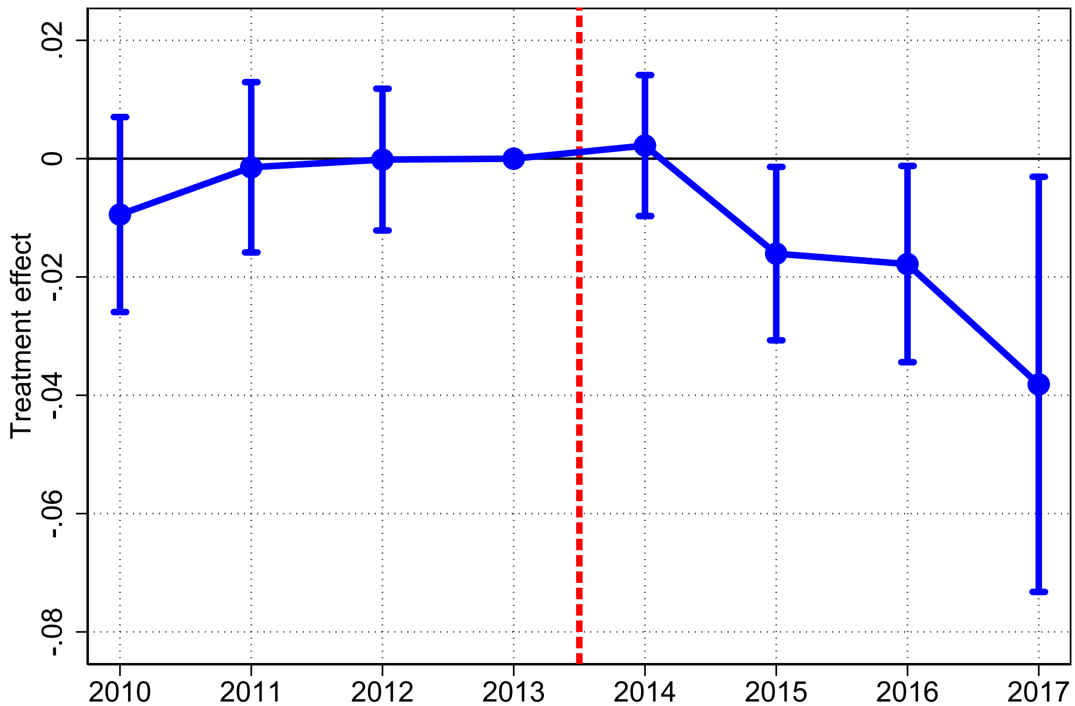
Figures

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



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 based on the difference-in-differences specification in (20), 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

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 *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 $\in \{0,1\}$		$\ln(1 + \text{total loan volume})$	
Sample	2010–2017			
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	Lead banks k in negative-rate currency areas from which firms j borrowed anytime in preperiod					
	2013–2015	2010–2017		2013–2015	2010–2017	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Deposit ratio$_k$ × After(06/2014)	-0.158**	-0.085*	-0.122*	-2.630*	-1.475*	-2.099*
	(0.076)	(0.048)	(0.061)	(1.382)	(0.852)	(1.108)
Deposit ratio$_k$ × 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	6,508	15,554	15,554	6,508	15,554	15,554

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). 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)
Deposit ratio × After(2014)	-0.019**	-0.077***	0.007**	0.011***
	(0.009)	(0.010)	(0.003)	(0.004)
Worker FE	Y	N	Y	N
Firm FE	Y	N	Y	N
Worker-firm FE	N	Y	N	Y
Year FE	Y	Y	Y	Y
N	70,137,681	67,731,621	65,253,153	63,505,552

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 two columns is the natural logarithm of the wage of individual i at firm j in year t. The dependent variable in the last two 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. 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 $\times$ After(2014) $\times$ 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 $\times$ After(2014) $\times$ 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 $\times$ After(2014)	-0.008			-0.008**		
	(0.007)			(0.003)		
Deposit ratio $\times$ Bottom 20% within firm	-0.136***	-0.142***		0.004	0.009**	
	(0.021)	(0.018)		(0.004)	(0.004)	
Deposit ratio $\times$ Middle 60% within firm	-0.112***	-0.106***		0.001	0.003	
	(0.015)	(0.013)		(0.003)	(0.003)	
After(2014) $\times$ 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) $\times$ 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	-0.107***	-0.050	-0.137***	-0.012	-0.028***	-0.009
	(0.031)	(0.037)	(0.031)	(0.007)	(0.009)	(0.010)
Deposit ratio × After(2014)	0.021	-0.017	0.060***	0.003	0.002	-0.017***
	(0.021)	(0.024)	(0.019)	(0.005)	(0.005)	(0.006)
After(2014) × Firm pay rank	-0.061***	-0.034	0.173***	0.001	-0.033***	-0.065***
	(0.023)	(0.028)	(0.023)	(0.005)	(0.006)	(0.007)
Worker FE	N	Y	N	N	Y	N
Firm FE	Y	Y	N	Y	Y	N
Worker-firm FE	N	N	Y	N	N	Y
Year FE	Y	Y	Y	Y	Y	Y
N	71,540,608	69,627,349	67,372,241	65,654,460	64,700,521	63,076,967

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. 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 firm j's state of incorporation. 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 firm j's state of incorporation. 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:

$$h_a(\tilde{p}) = \frac{\int_{\tilde{p}' \geq \phi_a}^{\tilde{p}} \overline{v}_a^*(\tilde{p}) \gamma_a(\tilde{p})}{V_a} \, d\,\tilde{p}' \tag{27}$$

$$h_a'(\tilde{p}) = f_a(w_a^*(\tilde{p}))\, w_a^{*\prime}(\tilde{p}) \tag{28}$$

$$f_a(w_a^*(\tilde{p})) = h_a'(\tilde{p}) / w_a^{*\prime}(\tilde{p}), \tag{29}$$

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

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

The acceptance probability for a firm offering w is

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

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

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

Then the firm's problem becomes

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

Therefore, the optimal wage and vacancy policy functions satisfy

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

Since the vacancy cost function $c(\cdot)$ is convex, and $\pi(\tilde{p}, w)$ in equation (31) is strictly increasing in $\tilde{p}$, then it follows from an application of the envelope theorem to equation (32) that $v^*(\tilde{p}, \cdot)$ 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. Under the 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. *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 2014–2016. Robust standard errors (clustered at the firm level) are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.