Heterogeneous employment effects of firms' financial constraints and wageless recoveries*

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Abstract

This paper studies the interaction of firm liquidity, employment and wages in light of credit supply disruptions. I establish that firms borrowing from banks highly exposed to the money-market freeze during the Global Financial Crisis received a shock to external liquidity, relative to otherwise similar firms. This constraint led to a significant drop in employment in affected firms, while wages did not fall relative to unaffected firms. In order to retain cash flow and build up internal liquidity, constrained firms cut labor cost predominantly by changing the composition of their labor force in favor of workers with lower wages. I provide evidence that this adjustment gradient is distinctly related to shocks to firms' access to liquidity. Employees separated from jobs with high residual wages are re-employed quickly, albeit at lower wages. This leads to sluggish wage growth even in unconstrained firms, and well into the recovery after a financial recession.

JEL classification: E24, E32, E44, J64

Keywords: business cycles, credit supply shock, heterogeneity, wage stickiness

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1 Introduction

Since the global financial crisis, many contributions have highlighted the large employment effects of disruptions in the credit supply to firms (Chodorow-Reich, 2014). There is accelerated interest in studying the interactions between frictional financial and labor markets, and what implications they have for cyclical dynamics of the economy. I show that not only do financially constrained firms decrease employment, but they change the composition of their labor force in a way that is consistent with deep and persistent slumps in employment after financial crises and anemic wage growth for an extended period of time thereafter.

I study how disruptions in the financial sector transmit to firms' ability to fund their operations and eventually labor market outcomes. I do so using administrative micro data that allows to link private-sector firms in Denmark to their bank lenders on one and their workers on the other hand. Bank lending is the prevalent source of outside liquidity in most Danish firms, and bank lending to non-financial corporations was reduced by almost 50% in the wake of the Great Recession of 2008/09. During the same time private-sector employment fell by 18%.

Two approaches are used to identify firms affected by unanticipated financial constraints: First, I exploit the fact that banks in Denmark were affected by the Global Financial Crisis (GFC) to different degrees. I build on Jensen and Johannesen (2017) in that I use the variation in that exposure and show that a cut in lending by exposed banks leads to a shift in credit supply to their pre-crisis borrowers that is orthogonal to the firm itself. Second, survey evidence suggests that retained cash buffers are an effective insurance against a funding squeeze during the crisis. Thus, the firms with a low degree of liquid assets as of 2007, relative to their fixed costs, are compared to those which do not rely on short-term external liquidity to stay liquid.

In both cases, I find that firms whose credit lines are withdrawn shrink in size to an economically and statistically significant degree. The effect on the level of employment is estimated to be up to 20% by 2011, and persists thereafter. A common structural interpretation is that financial crises prevent labor hoarding; the fact that firms can smooth employment over the business cycle to avoid costly displacements and future re-hiring cost. With squeezed funds, this is no longer possible, leading to a sharp downturns in employment. In the data, two thirds of the adjustment to the shock happens through a surge in separations, as opposed to a drop in hires. Even though the constrained, downsized firms generate lower profits, they manage to build up liquidity reserves to protect them against future funding shocks.

Making use of the possibility to match employers to the entire population and – to a large extent – their (not top-coded) wages, I study the heterogeneity of this labor market adjustment along the dimension of wages. In the firm-level estimates, wages do not

adjust to reduce the outflow of cash.[1] Instead, constrained firms change the composition of employment to a less costly labor force: Employment of workers with wages in the upper tail relative to their colleagues is reduced substantially more. While low-wage workers are *per se* more likely to be unemployed during recessions, high-wage workers are disproportionately affected by their employer's lack of funds. In order to improve their liquidity position as effectively as possible, constrained firms reduce employment of the most expensive workers most.

Labor market mobility in Denmark is comparable to U.S. levels, and I use the micro data at the individual job level to track the re-allocation after this shock. In contrast to U.S. evidence (Mueller, 2017), the pool of unemployed does not shift toward workers with previously high wages in my data. Instead, they have a lower likelihood of moving int ounemployment, but take wage cuts of up to 10% in their next jobs. In the macro view, wage growth is low in both constrained and unconstrained firms, albeit for different reasons: Constrained firms end up with a labor force that is composed of less costly workers, while firms with access to liquid assets can hire workers at lower rates. This mechanism introduces substantial persistence into workers' wage profiles and long memory of the labor market. It can partly explain why wage growth is sluggish even well into the recovery.

The rest of the paper develops as follows. Section 2 summarizes the recent and growing literature on employment effects of credit supply shocks and its importance for business cycles fluctuations. Section 3 discusses the identification of these shocks in bank-borrower and firm-level data, after which section 4 provides estimations for firms' responses. In particular, it documents the compositional change of the labor force in constrained firms based on their workers' previously negotiated wages. Section 5 moves to a job-level analysis to exploit the granularity of the Danish matched employer-employee data and studies labor market flows to and from constrained firms by worker type. I conclude by discussing the cyclicality of employment and wages and the macroeconomic implications.

2 Related literature

This paper bridges the gap between two strands of literature: the micro evidence of labor demand effects of firms' credit conditions and the macro movements of employment and wages of heterogeneous workers over the business cycle.

A growing literature is empirically investigating the real effects of financial shocks to firms using micro data. Typically, it is argued that sticky relationships between corporate borrowers and their lenders arise due to asymmetric information (Banerjee et al., 2017), such that a credit tightening by a lender cannot easily be substituted by lending elsewhere, lead-

[1] The literature finds that the degree of wage stickiness among incumbent workers is why firms adjust along the extensive margin in the first place (Schoefer, 2015).

ing to a decrease of credit supply at the firm level (Khwaja and Mian, 2008, Iyer et al., 2014).[2] The real effects of such shocks have been documented, for instance, on investment (Amiti and Weinstein, 2018) and, more closely related to this paper, employment Chodorow-Reich (2014). The latter finds that firms which used to borrow from highly levered banks through the U.S. syndicated loan market had a higher probability of having their credit lines cut after the financial turmoil of the GFC in 2008/09. These firms display a sharp contraction of employment relative to firms with otherwise similar characteristics, because employment requires the firm to fund the period between the creating a vacancy and receiving the cash flow generated by the match, similar to investment. This finding has been confirmed for other countries and identification strategies (Bäurle et al., 2017, Bentolila et al., 2018, Cornille et al., 2017, Melcangi, 2018). It is well-established that credit supply disruptions were crucial to explaining employment contractions during the Great Recession, particularly among smaller, less transparent firms (Gertler and Gilchrist, 2018, Siemer, 2019). Furthermore, the effects seem to propagate to unconstrained firms through local demand, are persistent and have a dampening effect on productivity (Huber, 2018), even though this transmission mechanism remains in the shadow.

This paper conveys the idea that the heterogeneity of the employment effects of funding shocks is a promising avenue to explore. For example, Barbosa et al. (2019) find that employment of high-skill workers falls at firms operating with banks which had unexpected pension obligations and therefore had to reduce credit supply. They attribute this finding to increased difficulties of constrained firms to attract workers with high human capital. The literature further finds that credit constraints disproportionately affect employment of workers on temporary contracts (Caggese and Cuñat, 2008, Berton et al., 2018, both for Italy). Caggese et al. (2019) look at labor force adjustments of financially constrained firms to exogenous productivity shocks to Swedish firms and conclude that, due to firms placing a higher weight on short-term returns, they fire workers with short tenure, who have lower current productivity but high expected productivity *growth*.

Moser et al. (2019) study worker allocations across constrained and unconstrained firms in Germany. They argue that the introduction of negative interest rates in the euro area in 2014 caused deposit-funded banks to reduce lending relative to banks relying on wholesale funding (Heider et al., 2019). The two main findings are that a negative credit supply shock decreases wage inequality between firms and increases it within. The first is attributed to the fact that low-pay firms are more risky, and thus receive relatively more

[2]It has been challenged whether Denmark has experiences a credit slump during the financial crisis in the first place, especially given its institutional framework of government-backed and bond-financed mortgage banks (Abildgren, 2012). However, Jensen and Johannesen (2017) have used a very similar identification strategy to this paper and conclude that household borrowing from their vulnerable house banks did indeed see loans decrease, interest rates increase and consumption fall by around 4%, pointing to the presence of a credit supply shock. I confirm this result for the supply side of the economy. While firms are more financially flexible than households, who typically borrow from a single bank, their borrowing horizon is much more short-run. Additionally, limited liability in firms potentially gives rise to larger degrees of relationship banking in firms compared to households, which exacerbates the pass-through of bank-level shocks to their borrowers.

credit than high-paying firms after a credit contraction. The latter is directly at odds with the results of this paper, which impliy firm-level inequality to fall after a funding squeeze. Structural differences in labor markets might explain these contradicting results, as the extensive margin of labor force adjustment is considerably more flexible than Germany's (Andersen, 2012).

A further key contribution of this paper is that it connects the micro findings to the (empirical and theoretical) macro literature on the cyclicality of employment and wages of heterogeneous workers. In this respect, it is closely related to to Mueller (2017), where the composition of the pool of unemployed shifts to workers with higher wages in their previous job in recessions. An explanation put forward for this phenomenon in the paper are indeed cash flow constraints. As this potentially increases the incentive to hire from said pool, it poses an additional challenge to the excess volatility puzzle in canonial search and matching models with productivity shocks (Shimer, 2005). Previously, it had been argued that a deterioration of worker quality among the pool of job seekers during recessions could address the Shimer puzzle (Pries, 2008, Ravenna and Walsh, 2012).

Petrosky-Nadeau and Wasmer (2013), too, have shown that financial frictions provide a promising avenue to exacerbate labor market volatility in light of productivity shock. Whether they be implemented as search cost in credit markets (Petrosky-Nadeau and Wasmer, 2013, 2015), an agency cost setting where vacancies are being financing with a constraint on firm net worth (Petrosky-Nadeau, 2014) or firm income (Boeri et al., 2018), they all have one feature in common: They increase the cost of vacancy creation when financial constraints are tight, and therefore have large employment effects.

The case of wages conditional on funding shocks is a particularly interesting one. Michelacci and Quadrini (2009) develop and test a model in which externally constrained – typically young – firms pay low wages in return for future wage growth, effectively borrowing from their employees. In contrast, in Quadrini and Sun (2018), a deleveraging shock deteriorates the bargaining position of the firm and therefore increases wages and reduces the incentive to hire, leading to larger volatility of employment. Schoefer (2015) proposes that wage stickiness among incumbents can create the need for layoffs of workers when firms become cash constrained, without the need to deviate from relatively flexible wages of new hires, which is a well-established empirical finding (Pissarides, 2009). I confirm the stickiness of incumbents' wages, even during large downswings such as the Great Recession. Since wages of new hires are more flexible, workers with previously high wages are hired from the pool of unemployed with a persistent cut in their nominal wage. This is consistent with a flattening of the Phillips curve, a key consideration in the conduct of monetary policy.

3 Identifying financially constrained firms

The GFC was characterized by disruptions in the financial intermediation process, particularly in the banking sector. Besides internal liquidity in the form of retained profits, firms heavily rely on access to external liquidity in order to fund payrolls and other operating cost, and bank credit lines are the principal source to do so (Lins et al., 2010). The banking crisis which unfolded in 2008 and 2009 interrupted this supply of credit. Accordingly, I use strategies to identify negative credit supply shocks at the firm level: the coffers of internal pre-crisis liquidity, as well as two measures on the health of the pre-crisis lenders. The following two subsections motivate and validate those strategies, all of which have been used previously in the literature.

3.1 Exogenous disruptions in bank credit supply

First, I use data on bank-borrower balances and variation in bank health to estimate credit availability to firm j by bank b. To obtain a measure which is independent of the borrower, I instrument credit supply in a lending relationship by the lender's credit supply to all other corporate borrowers in the data, similar to Chodorow-Reich (2014). Specifically, let $L_{j,b,t}$ be credit outstanding of j at b in period t, and $L_{-j,b,t}$ the lending of b to all other firms. I will then proxy the growth rate of credit with the respective growth rate of $L_{j,b,t}$:

$$l_{j,b,t} = \beta_0 + \beta_1 l_{-j,b,t} + u_t$$

$$l_{j,b,t} \equiv \frac{L_{j,b,t} - L_{j,b,t-1}}{0.5(L_{j,b,t-1} + L_{j,b,t})}$$

.

This instrument is referred to as IV $\mathcal{A}$. Because the firm's loans constitute a small part of the bank's overall lending, this instrument satisfies the exclusion restriction if credit demand is idiosyncratic to the firm. If credit demand is correlated across firms, however, this assumption might be violated. Therefore, I construct a second measure of loan supply shocks following Jensen and Johannesen (2017).

Consider a bank with high levels of lending (to all firms and households) relative to the amount of deposits, where the difference has to be financed through wholesale funding or equity markets, both of which became considerably tighter during the recession. This bank will have to cut credit, relative to its competitor with a more stable and long-term funding base. The structure of a bank's balance sheet prior to the global financial crisis therefore induces a shifter in banks' supply of funds which is plausibly orthogonal to the credit demand of its borrowers, something which is verified below. Let us define a measure

of bank health in 2007 as the ratio of total loans to deposits, i.e.

$$LTD_{b,07} = \frac{\text{loans}_{b,07}}{\text{deposits}_{b,07}}.$$

Due to the non-linear nature of this metric, a bank-invariant dummy $\mathbb{1}[LTD_{07}]_b$ takes the value 1 if either its exposure measure in 2007 was above the median of its competitors, or if it stopped lending altogether in the period between 2008 and 2011. It will be referred to as IV $\mathcal{B}$.

Data on banks and bank-borrower relationships Both instruments are brought to data relying on tax filings in which financial institutions in Denmark report amounts outstanding of unsecured loans and deposits at the end of the calendar year, as well as interest paid on loans and deposits over the course of said year. The data contains no information on other terms of the loan contract. The raw data is at the loan account level and covers unsecured loans to the corporate sector by banks as well as non-banks. The first part of the analysis is performed at the lending relationship level, where I sum over loan amounts and interest paid within a firm-bank pair. Later on, I will show that the transmission of credit carries over to the firm level.

The loan-level data is merged to balance sheets of 101 banks, collected by the Danish financial supervisory authority, which are publicly available. In doing so, I disregard non-bank and collateralized lending such as mortgages. To validate the loan-level dataset, I compare the sum of all loans outstanding within a bank-year to the aggregate number of loans to Danish non-financial corporations, which is reported to the central bank's Monetary and Financial Statistics (MFI). The correlation coefficient is 0.97, and also tracks the time series dimension of aggregate lending to the corporate sector well.

On the firm side, I match the data to detailed annual accounts (balance sheets and income statements, and employment) of private-sector firms that, at some point between 2003 and 2016, have at least 10 employees. This data is described in greater detail below.[3]

Danish financial markets Between 2003 and the end of 2008, bank lending to non-financial corporations according to the MFI increased by a factor of 2, while deposits grew at a substantially lower pace. Direct exposure to the market of mortgage-backed securities at the origin of the GFC was limited among Danish banks, liquidity decreased substantially when international money markets dried up. As a result, the Danish central bank injected liquidity into the market. Regardless, a range of banks became insolvent, and total lending to the corporate sector contracted by 15% from the peak through October 2009. A second,

[3]It should be noted already that not all firms have unsecured bank loans: Of the baseline firm sample, I can identify bank loans for only 46%, raising concerns of a potential selection bias in the sample. 53% (62%) of firms with at least 10 (50) employees are matched. The fact that even for large firms the rate of matches is well below 100% indicates that the reason is related to data reporting, rather than sample selection. In all regressions using the bank-borrower relationship data, I will exclude unmatched firms to minimize selection bias. However, I will complement the bank lending identification strategy with one that solely relies on the firm balance sheet data to confirm my results on the full sample of firms.

more gradual phase of credit tightening followed in the fall of 2010 and lasted through mid-2014, after which the level of outstanding loans was another 30% lower. The size of the increase in the loan portfolio has been very modest since. Note that the financial shock did not originate in the Danish corporate sector.

These movements matter because of the prevalence of bank lending in the funding structure of Danish firms. The median ratio of total debt to assets is 72% over the entire sample, whereas more than 3/4 of this amount has a maturity of less than 1 year. Short-term debt summarizes different sources of credit such as firm-to-firm lending (including accounts payable), export credit, government loans, or bank credit with and without collateral. While I have no data on collateralized loans, the possibility to match the uncollateralized loans from the bank-borrower relationship dataset onto other firm-level data is the most promising route to study shocks to external liquidity because of the short-term nature of these credit lines. The median firm that can be matched to a bank has a ratio of bank credit to its assets of 15%. Figure 1(b) shows the distributions of these different debt ratios across firms.

3.1.1 Credit market outcomes at the bank level

This section validates the choice of the bank health measure (IV $\mathcal{B}$) and documents lending behavior after the global financial crisis at the bank level.

For the measure of bank health to be a valid supply shifter, it is required that the instrument is uncorrelated with characteristics of the borrower, in particular its hiring decisions. If lenders specialize in terms of size, geographical location or riskiness of their borrowers, their loan/deposit ratios might be jointly determined with the outcome variable I study. In Figure 2, I show that this is not the case in the bank health measure I use. The distributions of firm size and growth, as well as the growth rate of debt and wages all overlap for firms borrowing from banks with high/low exposure banks for the period before the onset of the GFC.

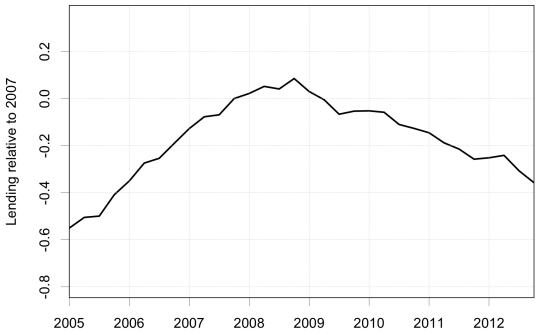
To characterize bank behavior throughout the period of de-leveraging during and after the banking crisis, I regress bank-level outcomes on $\mathbb{1}[LTD_{07}]_b$ interacted with yearly dummies and plot coefficients and clustered standard errors in Figure 3.

In Figure 3(a), the dependent variable is the log of the sum of loans outstanding to businesses in the bank-borrower micro data, with the year 2007 being the base level. There is no significant difference in the trend prior to the onset of the crisis. A wedge opens in 2008: Banks for which assets have been covered less by long-term funding sources such as deposits contracted lending significantly and permanently. At the same time, lending by non-exposed banks was stable, such that the exposed banks explain almost the entire decline in the aggregate quarterly time series of business lending, depicted in Figure 1(a).

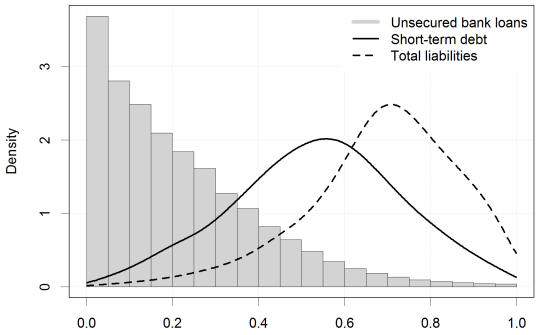
Could this be the result of risk-averse businesses avoiding to operate with risky banks? To

Figure 1: Credit market outcomes

(a) Aggregate lending to NFC sector



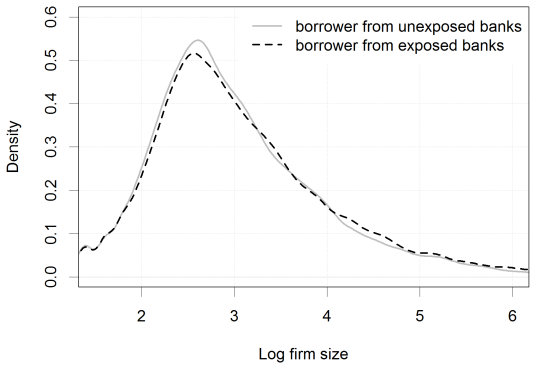
(b) Debt/asset ratios: Distribution



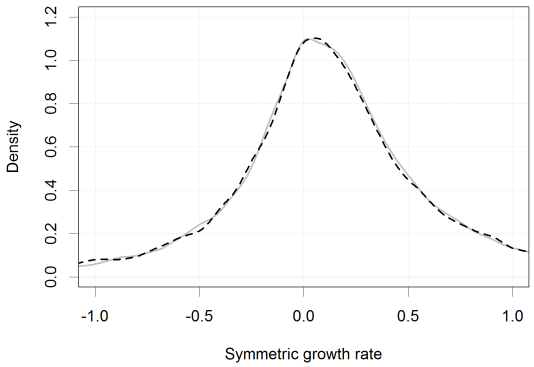
Note: Panel (a) shows the log of the quarterly time series of bank lending to non-financial corporations with residence in Denmark, relative to 2007q4. At the peak, this is equivalent to 30.7% of GDP. Source: MFI. Panel (b) is the empirical density function of different measures of debt relative to firm assets in the overlapping sample of bank credit and firm balance sheet data. Sources: Unsecured bank loans is the sum of matched loan balances from the micro borrower data. Short-term and total debt are reported in the balance sheet data, whereas the former summarizes debt to a host of creditors with a maturity of up to 1 year.

Figure 2: Borrower characteristics by bank health: Pre-GFC

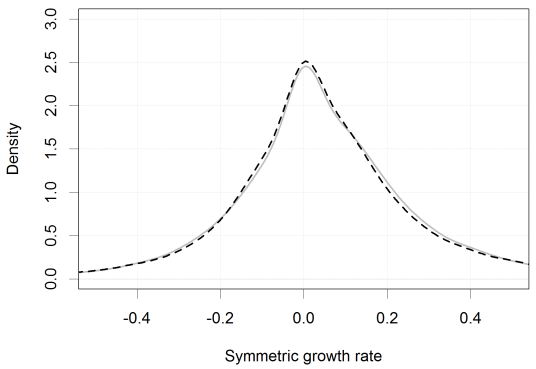
(a) Firm size (log employment)



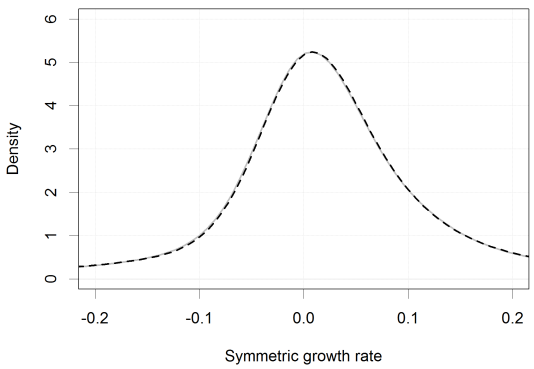
(b) Short-term debt ratio



(c) Employment growth



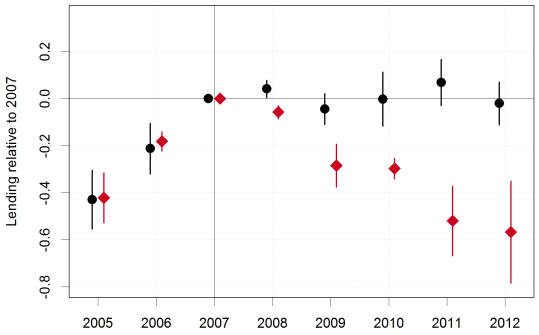
(d) Wage growth



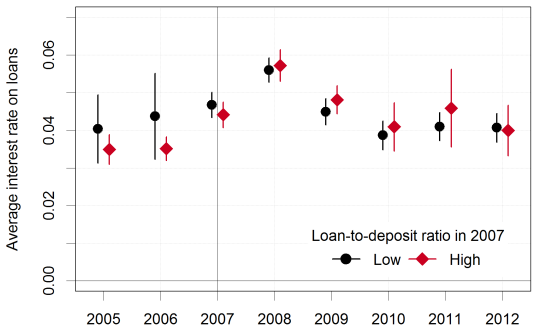
Note: Kernels of distributions of log employment, the ratio of short-term debt to total assets, employment and wage growth in the 2003-2007 subsample, by $\mathbb{1}[LTD_{07}]_b$, which describes whether the loan/deposit ratio of the firm's banks was above (exposed) or below (unexposed) the bank sample median.

FIGURE 3: CREDIT MARKET OUTCOMES

(a) Business loans by exposure



(b) Average interest rate on loans



Note: Coefficients and standard errors of a regression of loan market outcomes (log of loans to all corporate lenders in the micro data, and the weighted average interest rate on those loans) on a dummy indicating whether the bank had above-median exposure to wholesale money markets in 2007 as measured by the loan-to-deposit ratio, interacted with dummies for all years but 2007. The 101 banks are weighted by the size of their loan portfolio in 2007, and standard errors are clustered at the bank level.

rule out the possibility of a shift in aggregate demand for loans from the exposed banks, I use again the bank-borrower data of unsecured debt and calculate a relationship-level interest rate by dividing the interest paid throughout a year by the mean of current and lagged balances. The weighted mean of interest rates within a bank by exposure measure is depicted in panel (b). Interest rate developments are relatively similar and, if anything, increase in exposed banks.

Consequently, market shares of exposed banks decrease significantly, and so do other bank-level outcomes that are omitted but available upon request. The number of (new) clients at exposed banks decreases, even though the difference between exposed and unexposed banks is not statistically significant. I conclude that banks have been heterogeneously affected by the global financial crisis, and will next discuss how this heterogeneity transmits to differential credit supply shocks at their pre-crisis borrowers that are plausibly exogenous to the firms' performance, credit demand or hiring decisions, including labor supply.

3.1.2 Credit market outcomes at the firm level

The type of propagation relies on the existence of sticky lending relationships. In a frictionless credit market, a tightening of credit conditions of a pre-crisis lender could be fully compensated by increasing credit lines from one or more others. In a principal-agent credit market, however, borrowers and lenders form relationships, over the course of which informational asymmetries are reduces, and switching lenders becomes costly. The emergence of relationship lending has been studied using similar datasets, including the effects on employment (see for example Banerjee et al. (2017)).

Since the raw data is at the lending account, rather than the relationship level, I test

whether new loan accounts are opened at banks with which a relationship history exists. In particular, consider all newly opened loan accounts over the course of the sample, and define a dummy variable equal to 1 if the bank identifier is equal to the primary bank of the previous year, and zero otherwise. In a linear probability model, the constant describes the probability that new loans are taken up at banks with which the firm has operated previously.

Even after controlling for the bank's market share, a bank that used to be a firm's primary lender has a high likelihood of being the provider of the new loan, too. The estimated coefficient is 0.42, and thus very close to the estimate of Bharath et al. (2007).[4] Furthermore, this likelihood decreases with the number of lenders the borrower has had in the past and the size of the loan, all of which supports the hypothesis of information asymmetries, especially among small borrowers. When including only the most connected firms, i.e. borrowers with at least two lenders, the stickiness of lending relationships decreases and the importance of lender size increases significantly. However, 79% of firms in the dataset only have loans with one bank.

To test the first stage of shock transmission from banks to their incumbent borrowers more rigorously, I first regress loan amount growth of a firm-bank pair during the crisis on instruments $\mathcal{A}$ and $\mathcal{B}$,

$$\Delta l_{j,b,t} = \beta \, Z_t' + u_t,$$

where Z_t is either of the two instruments described. In the case of bank-lending to all other borrowers, this elasticity is estimated to be 0.2 (see Table 1, column (1)), suggesting that aggregate loan conditions by banks significantly impact a firm's capacity to borrow.

I exploit the fact that some, if not many, firms have multiple lending relationships, which allows to include a firm-year fixed effect and controls for unobservable firm characteristics such as idiosyncratic productivity or loan demand, provided that the firm's demand for credit is not specific to lender health (Amiti and Weinstein, 2018, Khwaja and Mian, 2008). Column (2) confirms the robustness to the inclusion of firm-year fixed effects.

The second panel of rows in Table 1 repeats the analysis at the firm-level. Since L is defined at the lending relationship level, I weight it the regressors by the lagged share of b in j's loan portfolio, $\alpha_{j,b,t-1}$, where

$$\alpha_{j,b,t} = \frac{L_{j,b,t}}{\sum_b L_{j,b,t}}.$$

The regression result suggests that a decrease in lending carries over to firm-level supply of external liquidity entirely.

For instrument $\mathcal{B}$, I preserve the binary nature of the treatment variable and let Z_t be the

[4] This is expectedly smaller than in the syndicated loan market in the U.S., in which large firms lend larger amounts of money from a relatively small pool of lead and supporting lenders. Chodorow-Reich (2014) estimates the coefficient to be 0.72 in this market.

Table 1: Credit supply at the firm level

	IV $\mathcal{A}$: Loans to others		IV $\mathcal{B}$: Loan/deposit ratio		
	(1)	(2)	(1)	(2)	(3)
Panel I: $\Delta l_{j,b,t}$					
$\Delta l_{-j,b,t}$	0.186***	0.200***			
	(0.015)	(0.040)			
$\mathbb{1}[LTD_{07}]_b$			−0.039***	−0.071***	−0.089***
			(0.013)	(0.016)	(0.035)
Panel II: $\Delta l_{j,t}$					
$\sum_b \alpha_{j,b,t-1} \times \Delta l_{-j,b,t}$	0.215***				
	(0.024)				
$\sum_b \alpha_{j,b,07} \times \mathbb{1}[LTD_{07}]_b$			0.000	−0.058***	
			(0.015)	(0.015)	
Year FE	Yes	No	No	No	No
Firm-year FE	No	Yes	No	No	Yes
Sample	2008-12	2008-12	2008	2009	2009
# observations	165,453	40,776	14,566	12,526	3,769
# firms	17,673	3,691	12,323	10,796	2,039

The dependent variables is the growth rate of gross lending within a firm-bank pair (panel I) and at the firm level (panel II), respectively. Instrument $\mathcal{A}$ is the growth rate of bank credit to all other borrowers of the bank, excluding the firm itself. Instrument $\mathcal{B}$ is a dummy taking the value 1 if the loan/deposit ratio was above the median of all banks in 2007. To aggregate instruments to the firm level, I weight regressors using α, which denotes the bank's weight in the firm's total bank debt. Firm-year fixed effects in column (A2) and (B3) absorb unobserved borrower characteristics, including credit demand. Standard errors are clustered by firm identifier. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

indicator $\mathbb{1}[LTD_{07}]_b$ describing the loan/deposit ratio in 2007. It shows that about half of the shock at the bank level presented in Figure 3 is transmitted to the relationship level: Credit to firms operating with highly levered banks in 2007 decreased by 3.9% more than those operating with healthier banks over the course of 2008. A year later, the decrease (relative to 2007) was 7.1% larger. Again, the effect is robust to including firm-time fixed effects for the firms with multiple lenders. At the firm level, the effect is insignificant in 2008, but the data for 2009 show that only a small part of the decrease from high-exposure banks could be substituted by loans from other banks.

3.2 Retained liquidity

While I have shown that bank liquidity shocks provide an exogenous shift in credit supply to their pre-crisis borrowers, not all firms rely on external liquidity to fund their operations. If this selection is positively correlated with the availability to access other sources of funding, estimates would be bias downwards. Therefore, I want to complement this analysis using an alternative identification scheme which solely relies on firm balance sheet data, allowing for a larger sample size.

Cash holdings, while not productive, act as an insurance against cash-flow shocks, in particular in times when credit becomes scarce and for firms that rely on short-term refinancing. In the spirit of Gilchrist et al. (2017), I use the lagged end-of-year liquidity ratio obtained from the longitudinal dataset of balance sheets of Danish private-sector firms as an explanatory variable to analyze differences in firm-level outcomes.

Balance sheet data The firm level-analysis relies heavily on the accounting statistics compiled by the Danish statistical office (DST) and covers a large sample of active corporations at an annual frequency. I will consider the sample period of 2003 through 2016. Primary sectors as well as financial services are excluded. The dataset is based on firms' tax assessments for variables relevant for taxation such as sales, profits, debt or equity. It is then augmented with other third-party reported information such as the number of employees and their remunerations, and detailed information on other income statement and balance sheet positions such as investment, liquid/illquid financial assets, tangible and intangible fixed assets, etc. are obtained for a subset of firms in regular surveys.

I constrain the sample to companies which during the sample period report having 10 or more employees (in full-time equivalents) at least once. This applies to between 25,000 and 29,000 firms per year, which account for more than 80% of private sector employment. Column 1 of Table A2 in the data appendix summarizes descriptives of accounting and employment statistics of these firms.

The baseline definition of the liquidity ratio of firm j in year t is defined as the stock of cash, $M_{j,t}$, at the end the period as a share of the nominal wage bill during the period.

$$\ell_{j,t} = \frac{M_{j,t}}{\sum_i w_{i,j,t} N_{i,j,t}} * 12$$

where i is the worker-related subscript. This definition emphasizes the fact that liquid assets are necessary to fund cash outflows the firm has committed to, and is equivalent to the number of months the payroll is funded by the stock of internal liquidity, should operations remain unchanged.

3.2.1 Survey evidence

To further motivate to choice of internal liquidity as a predictor of financial constraints, I apply an algorithm of unsupervised learning to a subset of the balance sheets matched to business tendency surveys.

Survey data on financial constraints The survey covers firms operating in the manufacturing and construction industries.[5] Firms respond to whether or not financial

[5]It is an extension to the monthly harmonized Business and Consumer Survey. Documentation and aggregated time series are provided by the Danish statistical office and referred to as KBI for the industry survey and KBB for the construction survey.

constraints pose a limitation to their production. They are repeatedly interviewed once a quarter, which is why the data are collapsed to a quarterly frequency. Figure 4(a) depicts the time series of the share of firms that perceive themselves to be financially constrained. Although the share of positive responses is low, it documents the squeeze in access to liquidity at the onset of the global financial crisis and its persistence therafter. Of the 1'300 firms reporting throughout the Great Recession, I am interested in predicting those who are financially constrained. Therefore, firms are matched to the latest previously available filing of annual firm accounting statistics. These include balance sheet items such as the liquidity ratio (as defined above), profits, inventories and investment (as shares of sales) and short-term debt as a share of the total balance sheet, as well as other firm characteristics, the 3-digit NACE industry, and geographical location. Further, the growth rates of short-term debt and employment, the average wage paid by the firm and the identifier of the main lending bank, if available from the bank-borrower micro data, are included as predictors.

Random forest A random forest is trained on this data. The advantage, as opposed to parametric estimation with a binomial distribution, is that it allows for higher-order interactions of these features.[6] Building 1,000 trees and allowing to randomly split on 4 variables at each split, the algorithm has an accuracy rate of predicting the survey response of 96.4%.

Permuting each variable and comparing the accuracy rate thereafter reveals that the liquidity ratio at the end of a year is the single most powerful predictor of whether or not a firm will have binding credit constraints subsequently (Figure 4(b)). If disregarded, the accuracy rate falls by 0.65%, which implies an increase of the error rate by a fifth. The algorithm further highlights two more variables related to cash flow: the stock of final goods inventories and profits made throughout the previous year.

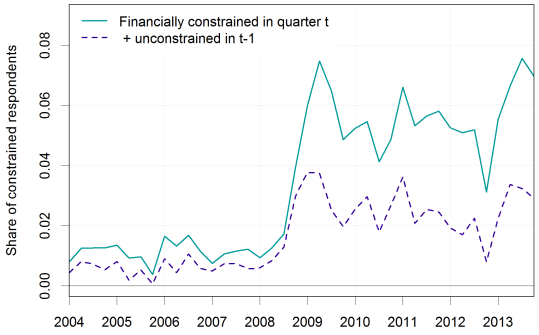
Treatment I classify firms according to their pre-crisis liquidity ratio ℓ_{07}, and consider, in the baseline specification, firms that have a liquidity ratio lower than the median of firms. Most firms operate with low liquidity buffers: The median across all firms is equivalent to 1.7 monthly payrolls. Results are robust with respect to alternative definitions of the cutoff, for example the median of competitors within an industry, or alternative definitions of the liquidity ratio.

High- and low-liquidity firms differ in terms of the pre-crisis characteristics. Panel (c) of Figure 5 shows that low-liquidity firms are larger. They are also more highly levered. In contrast, the growth rates of both employment and debt show very similar distributions for both groups. In order to compare firm-level outcomes such as the labor force adjustment throughout the Great Recession, it is crucial to control for those differences in the levels.

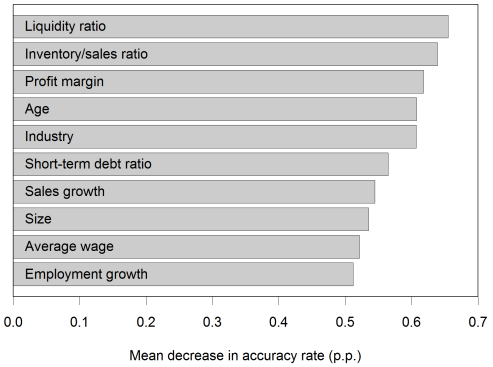
[6] Even in a logit model, the average marginal effect of a low liquidity ratio on having a positive survey response is significant.

Figure 4: Perceived financial constraints and their predictors

(a) Share of reportedly constrained firms



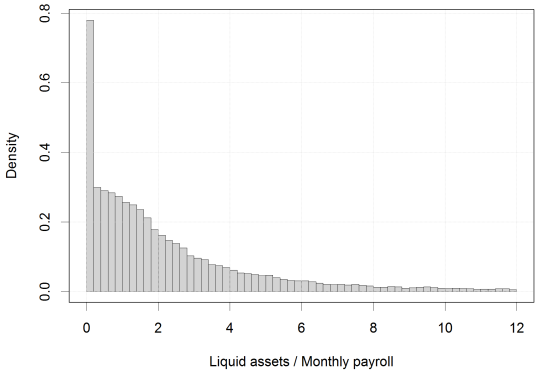
(b) Random forest feature importance



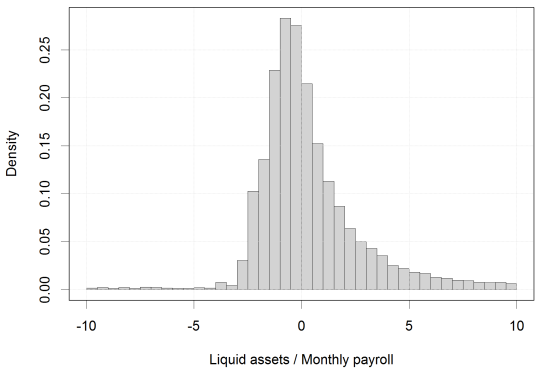
Note: Panel (a) depicts the share of firms responding positively to whether or not they currently perceive financial constraints to be limitations to their production. The dashed line indicates the share of firms that do so but did not in previous interviews. Panel (b) ranks predictors by the loss of accuracy in a classification model predicting this financial constraint response, permuting each feature separately.

Figure 5: Borrow characteristics by liquidity ratio: Pre-GFC

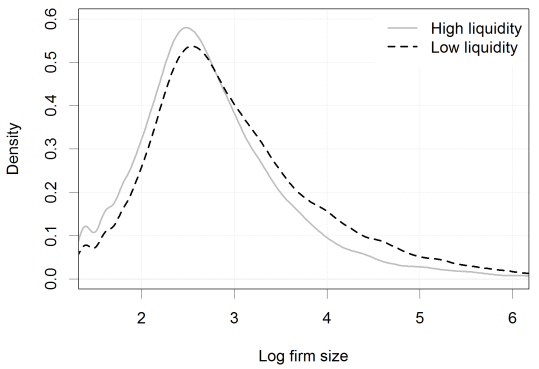
(a) Firm size (log employment)



(b) Short-term debt ratio

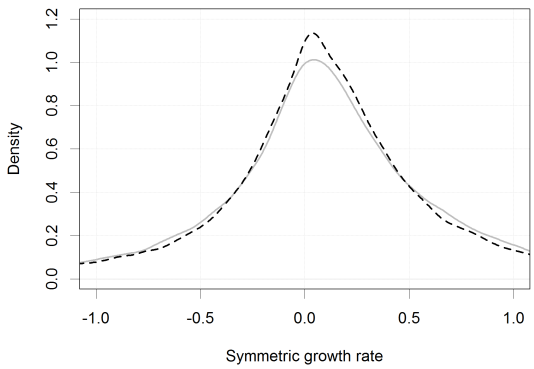


(c) Firm size (log employment)



p

(d) Short-term debt ratio



Note: Panels (a) and (b) show the cross-sectional distribution of liquidity ratios, (un-)adjusted for the firm's industry. The lower panels contain kernels of distributions of log employment and the growth rate of short-term debt in the 2003-2007 subsample above and below the liquidity median.

4 Labor force adjustments

To investigate the effect of this negative shock in credit supply on the size and composition of firms' labor force, I use matched employer-employee data, after which I present firm-level regression results using the above described instruments.

Matched employer-employee data This data covers all (anonymized) employer-employee matches of Denmark's private sector, each year in November. On the employer side, I use the sample of private sector firms for which I have balance sheet data described above. On the employee side, I observe the workers' amount of hours worked and total compensation over the course of the year (provided she is employed in November), as well as the occupation (according to the standardized ISCO classification). Other relevant registers at the individual level contain the highest completed level of education, age, and a variable on how many weeks throughout the calendar year the worker was supported by unemployment benefits. I only consider the workers between 25 and 60 years of age, and disregard jobs with an amount of hours lower than the equivalent of one full-time month.

I define a new match as the first observation of a worker-firm pair and a separation as the last. I further distinguish between job-to-job transitions (EE) if, in the year after a separation, the worker is linked to a new firm identifier (regardless of whether the firm is in my sample) and did not receive unemployment support in that or the previous year. If the worker has held multiple jobs in November of one year but only one in the next, the terminated job is considered an EE transition.

I observe hourly wages paid for a subset of approximately 70% of jobs in each year. They are obtained from the labor market survey of the Danish statistical office.[7] When studying compositional effects, I will bin workers by the last reported hourly wage I observe up to 2007. For the purpose of the analysis in this section, I collapse the number of total employees, hires, separations, and employment in each 2007-wage bin to the firm-year level.

I list the exact sources of micro data registers in Table A1 in the appendix and present descriptive (time series) statistics. To summarize, employees matched to the sample firms cover more than 40% of aggregate employment in Denmark.[8] The matched and full samples show very similar dynamics over the course of the recession: employment in both sample decreases by 300,000 employees from the peak of 2007 to the trough in 2009. Because the private sector contributed most to the job losses in the respective time period, firm-level outcomes can be interpreted in light of their implications for macroeconomic outcomes.

[7] Wage information from annual tax filings is available for the whole population. However, Lund and Vejlin (2016) have documented performance issues with this measure of hourly wages. My data are not prone to these issues.

[8] Note that Denmark has a large public sector, which is excluded from the firm data. The sample covers 80% of employment in the nonfarm business sector.

In the ensuing analysis, the relevant outcome variables are counted at the level of the firm. The first of these outcomes is employment.

4.1 Effects on aggregate employment

Table 2 summarizes the effects of a shock to credit supply on firm employment. In columns (1) and (2), I perform a regression of the following form:

$$\Delta n_j = \beta \Delta l_j + \gamma X_j' + \delta_k + \zeta_c + u_t, \tag{1}$$

where Δn and Δl are the symmetric growth rates of employment and bank credit between 2007 and 2009.

$$\Delta n_j \equiv \frac{N_{09} - N_{07}}{0.5(N_{07} + N_{09})}$$

This definition has the advantage that growth rates are symmetric, and bound between -2 and 2. It allows to include firms exiting the market in 2008 or 2009, in which case their employment growth takes the value -2.

The loan supply measure is instrumented, in column (1), by the growth rate of loans to all other borrowers by firm j's banks from 2007, weighted by the respective share α. In column (2), I use the loan/deposit ratio of all banks in 2007, and set the treatment variable equal to 1 if the weighted measure is above the median across banks. As already established in Table 1, both instruments predict firm-level credit outcomes, and the 2SLS shows F-statistics that are considerably above critical values for maximum bias of 5%.

The vector of controls includes balance sheet items in 2007: the ratio of short-term debt to total assets, bins for the cash over fixed cost ratio, and inventories (as a share of sales) that could potentially easily turned into liquid assets. Additionally, I include a number of fixed effects, most importantly for 228 industries k at the 3-digit NACE code level to control for industry-specific demand changes and for 29 commuting zones c.

For both the continuous and categorial measure of bank health, the effect on employment is economically and statistically significant. Holding all else fixed, borrowing from a bank that shifted credit supply inwards during the GFC resulted in employment that was 6% lower than firms borrowing from healthier lenders. The fact that more leveraged firms contracted significantly more further highlights the importance of leverage shocks.

The size of these effects at the micro level are larger than in (Chodorow-Reich, 2014), where the average firm has 3,000 workers. Siemer (2019) estimates an effect of 4% on a small-firm sample ($\leq$ 50 workers), albeit using a different identification strategy. My results are marginally higher than the direct employment effects estimated by (Huber, 2018). They are also macroeconomically meaningful: Over the respective period, employment decreased by 11% in total and by 18% in firms in the firm data (comparable to the non-farm business sector).

The sample is restricted to the firms that can be matched to a bank loan in 2007 to avoid an endogenous selection of the treatment variable. To the extent that unmatched firms do not have any bank loans and are thus not affected by a shock to credit supply, these estimates should be considered a lower bound. I can extend the sample by considering the pre-crisis level of retained liquidity instead of the health of connected banks. This is done in column (3) of Table 2. I estimate it directly using OLS because the first-stage effect of this measure is less compelling, as it is unclear in both theory and the data whether the amount of lending of these firms should increase or decrease.[9] Trying to control for as many variables as possible, having a liquidity ratio ℓ below the median within the firm's industry in 2007 resulted in a decrease of employment by 11% within two years. This finding is line with Bäurle et al. (2017), who estimate demand-employment elasticities under financial constraints, and find larger estimates for internal relative to external liquidity constraints. According to specification (3), firms with higher stocks of final goods inventories were able to generate more cash flow and keep workers on the payroll (Gertler and Gilchrist, 1994, Kashyap et al., 1994).

To study the dynamics beyond this 2-year window, I re-run the regression as a difference-in-difference estimation on the full panel of firms, rather than the 2009 cross-section.

$$\Delta n_{j,t}{}^{10} = \beta(T_j \times \gamma_t) + \delta_{k,t} + \zeta_{l,t} + \eta_j + u_{j,t} \tag{2}$$

In the figures presented as follows, I use IV $\mathcal{B}$ as the treatment variable T, but the main results are robust to using the other binary variable describing internal liquidity at the end of 2007 (see Figure A5 in the appendix). Beyond the industry demand control, this specification allows the inclusion of firm fixed effects (η_j) to control for unobserved heterogeneity, for example in time-independent firm productivity.

Figure 6 shows, first, that the y/y growth rate of employment is similar across firm's lending from high and low exposure banks prior to 2007. Second, the firms receiving shocks to external liquidity due to their banks' exposure downsize throghout the Great Recession. The effects is significant for all the years up to and including 2010, and the point estimates imply a permanent 20% reduction in firm size.

In a model with flexible wages and homogenous workers, such a fall in labor demand would reduce wages. However, repeating regression (2) with the average wage paid by the firm as the left-hand side variable shows no significant difference, neither prior nor during the Great Recession (similar to Huber (2018)). This holds true if I consider the average wage of incumbent workers and new hires (for firms that do hire) separetely. The main contribution of this paper is to put forward an explanation for this wage rigidity conditional on the credit supply shock: The differential effects on labor demand for heterogeneous workers

[9] On the one hand, liquidity-constrained firms would like to fund their continued operations by obtaining outside loans. On the other hand, low demand and cash flow might make it questionable if these loans are bearable.

[10] Consequently, $\Delta n_{j,t}$ now is the one-period geometric growth rate $(N_{j,t} - N_{j,t-1})/(0.5(N_{j,t} + N_{j,t-1}))$

Table 2: Employment outcomes in 2009

	IV $\mathcal{A}$ (2SLS)	IV $\mathcal{B}$ (2SLS)	Liquidity (OLS)
Dep. var.: $\Delta n_{j,b,07-09}$	(1)	(2)	(3)
$\Delta L_{-j,b,07-09}(\Delta \hat{L}_{j,b,07-09})$	0.064***		
	(0.009)		
$\mathbb{1}[LTD_{07}$ above median$]_b(\Delta \hat{L}_{j,b,07-09})$		0.063***	
		(0.007)	
$\mathbb{1}[\text{low } \ell_{07}]$			−0.111***
			(0.008)
Short-run debt ratio$_{j,07}$	−0.278***	−0.290***	−0.065***
	(0.024)	(0.023)	(0.007)
Inventory/sales$_{j,07}$	−0.092	−0.031	0.180*
	(0.127)	(0.123)	(0.098)
Employment$_{j,07}$	0.000	−0.002	−0.001
	(0.000)	(0.002)	(0.002)
Liquidity bin fixed effects	Yes	Yes	No
NACE3 sector fixed effects	Yes	Yes	Yes
Commuting zone fixed effects	Yes	Yes	Yes
# firms	9,980	10,833	25,123
First-stage F-statistics	46.53	65.07	
Adj. R^2	0.069	0.068	0.045

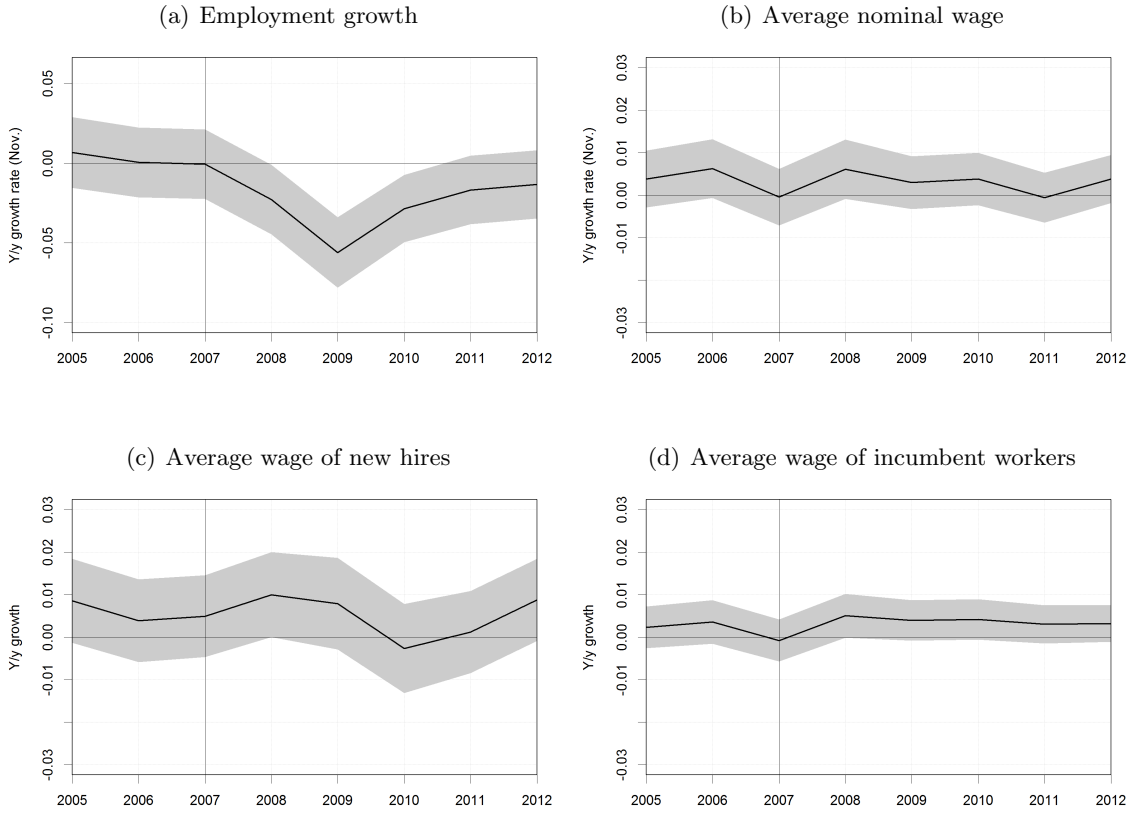
Note: The dependent variables is the geometric growth rate of the sum of matched employees between November 2007 and 2009. The first two columns perform a 2SLS estimation where the 2-year growth rate of bank credit is instrumented by the weighted growth rate of lending to other firms by the firms' banks (column 1), and a dummy for whether the firms' banks in 2007 had a weighted loan-to-deposit ratio above the median of all 101 banks (column 2). Firms that cannot be matched to a lending bank are excluded from the regression. Column (3) is an OLS regression on a dummy indicating whether the firms' liquidity ratio was below the industry-adjusted median. Standard errors are clustered by industry. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

that is specific to a liquidity shock masks the down-ward pressure on wages at the firm level.

Other firm-level outcomes Before proceeding to this compositional effect, I repeat the difference-in-difference model for a number of other firm-level outcomes regarding labor market and cash flow variables. Figure A3 includes the log number of hires and separations and suggests that, contrary to many labor market models with constant separation rates, they account for a larger share of the decline in employment than the drop in hiring, which only manifests in 2009. Separations in constrained firms increase 10% above the level of unconstrained firms. Unfortunately, the data does not allow to distinguish between quits and layoffs.

Operational profits react with a lag. Downsized firms generate an estimated 10% lower profits in 2009 due to the funding shock. Dividends and investments fall, too, even though it is difficult to establish a statistically significant effect. Interestingly, the amount of

FIGURE 6: DID REGRESSION RESULTS: EMPLOYMENT AND WAGES



Note: The black line represents difference-in-difference estimates of a negative credit supply shock, measured by the weighted loan/deposit ratio of a firms' banks in 2007. The left-hand side variables are the annual symmetric growth rates of employment (since November of the previous year, panel (a)) and the average hourly wage paid at the firm in the respective year (panel b), paid to newly hired workers (c) and incumbents workers (d). The grey bands represent 95% confidence intervals of the point estimate. Standard errors are clustered at the firm level.

liquidity hoarded by firms hit by the funding shock increases and plateaus 10% above the 2007 level (Kahle and Stulz, 2013). This emphasizes the trade-off credit-constrained firms face between retaining their labor force to generate cash flow and accumulating cash reserves simultaneously.

Figure A5 contains the same set of results by pre-crisis internal liquidity. Separations surge in low-liquidity firms and employment drops sharply. However, the pre-crisis difference suggests that this measure is not entirely free of endogeneity bias: Employment growth in the firms with low liquidity, which I classify as constrained, exhibit 4% higher employment growth in 2006, which might indicate an over-accumulation of workers and a resulting squeeze in liquidity. Yet, even in this case, where one could expect nominal wages to grow excessively in the boom, the average wage at the firm level does not fall significantly.[11]

[11] Additionally, I highlight the non-linearity of the liquidity-employment nexus in the same section in the appendix. In boom times, the elasticity is small, and the mechanism presented in Table 2 are by far the strongest during the recession.

4.2 Labor force composition

I provide evidence of a novel stylized fact that the composition of the labor force in constrained firms shifts toward less expensive workers. To do so, I assign workers to ten bins according to their wage in 2007, and I refer to those bins as $q_{w,07}$. Thereafter, I collect the stock of employees for each firm-wage bin cell and regress symmetric growth rates of these composites as in 2.

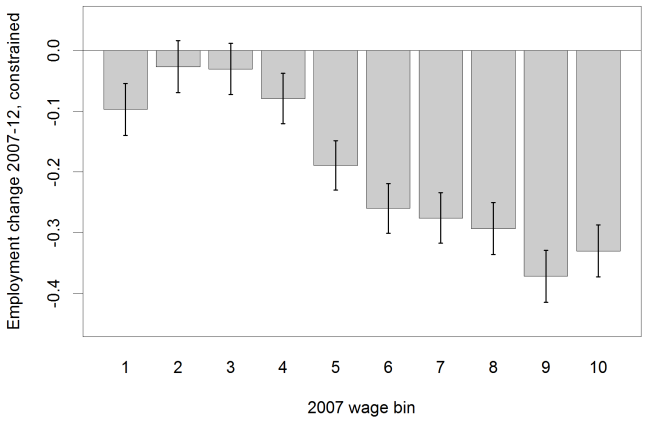
$$\Delta n_{j,q,t} = \beta_q \mathbb{1}[q_{w,07}] \times T_j \times \gamma_t + \delta_{k,t} + u_{j,q,t} \tag{3}$$

The interaction of the treatment term with an additional dummy for each q will give an estimate of labor adjustment for each of those bins separately.

Figure 7 shows estimates of the vector β_q for the year 2012, when the growth rate of firm-level employment (according to the previous section) has stabilized. The 2007 wage bin (from lowest to highest) is depicted on the x-axis. Relative to unshocked firms, the ones receiving a shock to liquidity disproportionately reduce employment of workers with previously high wages. The growth rate of workers with the lowest and highest wages are significantly different, with the latter falling three times as much as low-wage employees. Figure 8(a) tests whether this effect is driven by firm piling up too many high-wage workers prior to the onset of the credit tightening. In this case, the partial effects on either side of the wage spectrum are not significantly different from zero.

FIGURE 7: HETEROGENEOUS EMPLOYMENT EFFECTS BY PRE-SHOCK WAGE

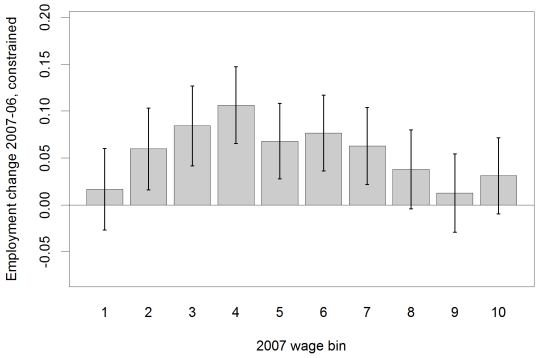
(a) Composition changes, 2012 rel. to 2007



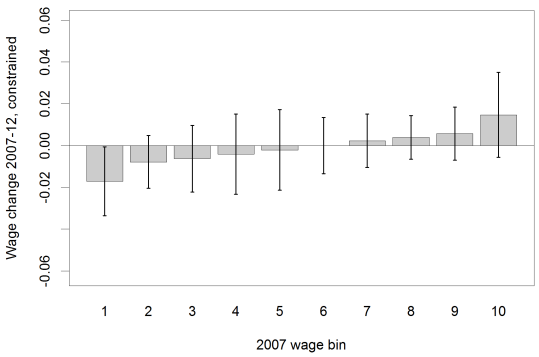
Note: Difference-in-difference estimator for each wage bin of workers in 2007. The dependent variable is the growth rate of employment in each firm-wage bin pair between 2007 and 2012 Therefore, estimates show the change in labor force composition *relative* to unconstrained firms. The greay bars denote point estimates, and black whiskers represent 95% confidence intervals. Standard errors are clustered at the firm level.

FIGURE 8: PRE-TREND COMPOSITION AND WAGE RESPONSE

(a) Composition changes, 2007 rel. to 2006



(b) Wage changes, 2009 rel. to 2007



Note: Difference-in-difference estimator for each wage bin of workers in 2007. The dependent variable in panel (a) is the growth rate of employment in each firm-wage bin pair between 2007 and 2006, respectively. In panel (b), it is the average growth rate of wages paid to workers in the respective bin between 2007 and 2009, given that they were employed in both periods. The greay bars denote point estimates, and black whiskers represent 95% confidence intervals. Standard errors are clustered at the firm level.

How should we interpret these findings in light of existing evidence and economic theory? One theory is suggested by Caggese et al. (2019). Binding credit constraints increase the opportunity cost of liquidity and discount the future benefits of a job more heavily. In light of this, jobs that pay high wages would be discontinued disproportionately. This effect would be exacerbated if the return to a high-wage job, say a researcher, lied further ahead in the future than the return generated by a typical low-wage job. A decrease in labor supply to financially constrained firms could offer an alternative explanation, as employees are anxious to receive wage cuts in the future (Barbosa et al., 2019). However, I provide suggestive evidence below that raises concerns about labor supply as a driver of the gradient presented in Figure 7. In short, displaced high-wage workers experience large decreases in their wage in a new job.

Carlsson and Westermark (2016) show that wage rigidities of incumbent workers, as opposed to wages of newly hires workers as in Pissarides (2009) matter for employment adjustment to shocks if the separation rate reacts endogenously. My data allows me to test this in light of a financial shock, which has large effects if incumbent wages are rigid and workers are paid with the liquid asset Schoefer (2015).

I can test to what extent my finding is contributed to by higher wage rigidities among high-wage workers, which could explain why labor cost is cust more sharply at the extensive margin. Take regression 3 and replace the left-hand side with the average wage growth rate of workers within the respective bin $q_{w,07}$. This automatically selects incumbent workers only.

Figure 8(b) plots the equivalent vector of estimated coefficients. The point estimates do point to the fact that workers that already are highly paid managed to increase their wages from constrained firms. A possible rationale could be provided by Quadrini and Sun (2018)

who argue that a deleveraging shock increases the bargaining power of workers. However, wages of the lower bins do fall slightly; and effects are rather imprecisely estimated and not significantly different from each other.

I conclude from this exercise that wage stickiness of incumbent workers is present, and is indeed an explanation for large effects on employment, but it cannot alone explain the differential findings provided in Figure 7.

The dispersion of wages can represent a host of different heterogeneities of workers and firms such as dispersion in actual (observed or unobserved) productivities or frictional competition in the labor market (Bagger and Lentz, 2019). To test whether the gradient observed above is driven by fundamental productivity or "excess wages", I perform the same analysis on deciles of workers sorted by a measure of fundamental worker productivity and a wage measure residualized of this worker heterogeneity. I perform a two-way fixed effect regression on job observations of worker i and firm j, as in Abowd et al. (1999). The regression takes the following form

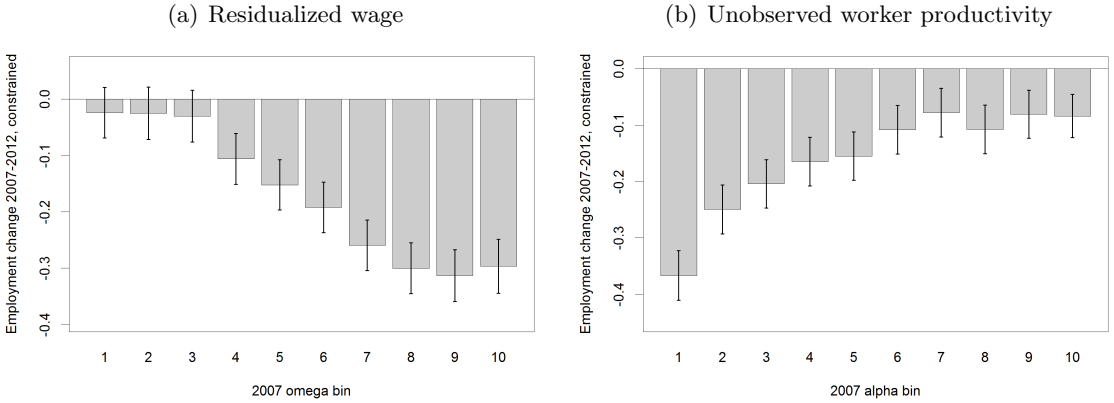
$$w_{i,j,t} = \alpha_i + \psi_{j(i,t)} + \beta X'_{i,t} + \omega_{i,j,t}$$

The vector X includes dummies age, tenure within the current job, overall labor market experience, the occupation and the typical years of schooling to complete the highest completed education. Since this regression can only be identified on the connected set of workers with at least two jobs spells, the unobserved worker productivity α_i and the residualized, job-specific wage $\omega_{i,j,t}$ can only be assigned to a subset of the data.

I then collect again the firm-specific composition of each of 10 bins of these variables, denoted $q_{\alpha,07}$ and $q_{\omega,07}$, and proceed as in regression 3. Figure 9 presents the results, suggesting that the negative gradient of the employment response is not driven by inherent, unobserved worker ability α. In fact, it appears as though employment of workers with a low estimated α falls the most, whereas constrained firms seem to hold on to most of the highest types. In contrast, the negative gradient originates from workers with high residual wages. Note, however, that the AKM approach is silent about the exact nature of ω, as it could represent both match-specific productivity (sorting) or the worker's rent extracted from the frictional surplus.

The results presented here have used the pre-crisis lender exposure to the banking crisis to estimate the differential effects of a credit supply shock on the composition of the labor force. The main result, namely that contrained firms adjust labor cost predominantly by reducing employment of the most costly workers (especially relative to their productivity), is robust to using the alternative classification using internal liquidity.

FIGURE 9: HETEROGENEOUS EFFECTS BY PRE-SHOCK WORKER CHARACTERISTICS



Note: Difference-in-difference estimator for each "ability type "(α) and "residual wage"(ω) bin of workers in 2007. The dependent variable is the growth rate of employment in each firm-group bin pair between 2007 and 2012. Therefore, estimates show the change in labor force composition *relative* to unconstrained firms. The greay bars denote point estimates, and black whiskers represent 95% confidence intervals. Standard errors are clustered at the firm level.

4.3 Benchmark labor demand shock

These findings contradict the fact that employment of low-wage (Bils et al., 2012) and low-skill (Keane and Prasad, 1993, Mueller, 2017, online appendix) workers shows a higher degree of procyclicality over the business cycle. Therefore, I want to contrast the results of labor force adjustment after financial disturbances from Section 4.2 with a different source of business cycle fluctuation. Contrary to the financial shock studies in detail above, the effects of a local labor demand shock has by far the strongest effects on workers with the lowest wages.

Bartik instrument I construct a shift-share instrument based on the notion that local employment growth rates can be predicted by an interaction of local industry employment shares with national industry employment growth rates. If $s^N_{k,l,t-1}$ is the employment share of industry k in location l in a pre-determined year t-1 and $\Delta n_{k,-l,t}$ is the national employment leave-on-out-growth rate of said industry, then firms in a region with a high exposure to that industry will experience a larger effect of aggregate variations in that industry.[12] These changes are unrelated to labor supply to the firm, but do not require to take a stance on the interpretation of the source of the underlying shock. The instrument has been used to study local labor market effects in many contexts, including rising competition to local manufacturers by Chinese imports (Autor et al., 2013) or sectoral reallocation of labor (Chodorow-Reich and Wieland, forthcoming).

[12]Following Goldsmith-Pinkham et al. (2019), I exclude the region itself when calculating the national growth rate because of the finite sample of locations.

Table 3: Local labor demand shock: 2SLS estimates

	Bartik (2SLS)	Bartik (2SLS)
Dep. var.: $\Delta n_{j,t}$	(1)	(2)
$\Delta \hat{n}_{k,l,t}$ (Shift-share)	0.461***	0.689***
	(0.024)	(0.047)
Firm fixed effects	Yes	Yes
Sample	2003-2016	2008-2009
# observations	343,019	55,865
# firms	39,229	29,610
First-stage F-statistics	36.41	21.29
Adj. R^2	0.077	0.148

Note: The table reports 2SLS regressions of local labor market shocks and firm-level employment of all types of employees. The growth rate of the local labor market is instrumented using the interaction of the industry's share of employment in the commuting zone and the leave-on-out growth of the industry's employment in all other commuting zones (shift-share). Standard errors are clustered by industry. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The first stage is specified as

$$\Delta n_{k,l,t} = \sum_{k} s^{N}_{k,l,t-1} \Delta n_{k,-l,t} + u_t.$$

Data Danmarks Statistiks allocates all 98 municipalities into 29 commuting zones based on people's actual commuting behavior, which I denote l.[13] Both the location and the industry k in which firms operate are taken from the accounting registers, and the latter are defined at level 3 of the NACE/ISIC industry classification system. The growth rates Δn of each sector are calculated by aggregating employment N over all firms for which employment data is available (not just the firms in the baseline sample used throughout the paper).

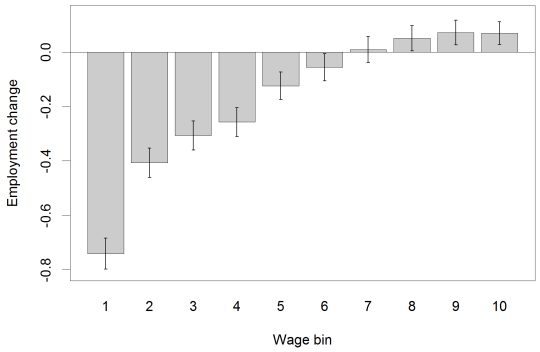
Results To observe the effect on employment of any kind at the firm level, I regress the firms' outcome $\Delta n_{j,t}$ on local labor demand growth, instrumenting with the above described shift-share product. Table 3 confirms that firm-level employment co-moves with local labor market conditions. A firm adversely affected by such a shock therefore cuts employment.

Moreover, the compositional effects are the opposite of the financial shock presented in Figure 7. To show this, I again repeat the exercise at the level of firm-bin level, with bins being constructed using employee's relative position in the wage distribution of the firm. For each year, I construct the growth rate of employees in that bin $\Delta n_{j,qt}$ and regress it

[13]The algorithm selects commuting zones, among other requirements, in order to maximize the share of people who live in the same region they work. The average of the resulting shares based on the year 2014 is 76%. Workers have become more mobile and the amount of commuting zones has declined steadily, making it important to use a timely classification.

FIGURE 10: HETEROGENEOUS EMPLOYMENT EFFECTS BASED ON PRE-SHOCK WAGE

(a) Compositional changes



Note: Growth rates of firm-level employment to a local labor demand shock of -1, for 10 bins of workers grouped according to their wage position within the firm prior to the shock. Estimation is performed using a Bartik instrument.

on the above instrument. The coefficient obtained for low-wage bins is much larger and strikingly different from workers in the center and upper tail of the distribution, who are much less affected. Figure 10 shows the negative of estimated coefficients, showing the much higher cyclicality of low-wage employees.

In contrast, Carlsson et al. (2016) find that in response to a TFP shock (to which overall wages do adjust), firms do not change the composition of their labor force. Overall, I thus conclude that the compositional changes financially constrained firms engage in is different from other sources of business cycle fluctuations.

5 Job flows and aggregate implications

This section explores how the labor market as a whole adjusts after some of the firms become financially constrained. It relies on the same data as described in Section 4, but the unit of analysis is now at the job level (i.e. worker i and firm j), as we want to explore worker flows from shocked firms.

Worker flows Separations in constrained firms increase, and the adjustment is disproportionate for high-wage workers. In order to study the flow of these workers, I classify each separation as a transition into unemployment (referred to as EU) if the worker cannot be matched to a firm in the subsequent year, or if the worker has received unemployment benefits throughout that year. Unfortunately, the data do not allow me to re-construct the precise timing of these unemployment benefits. Furthermore, the data on unemployment spells should be considered incomplete, as the first safety net of unemployment insurance in Denmark is organized privately. A regression of the following form for all separations

of 2008 and 2009 is run in order to retrieve the likelihood of a worker moving into unemployment based on her previous firm and wage.

$$\mathbb{1}[EU_i|s_i = 1] = \beta_q \, \mathbb{1}[q_{w,07}]_i \times T_j + u_i \tag{4}$$

T is again the indicator variables for whether the firm lendt from an exposed bank prior to the GFC. Figure 11(a) presents this estimated coefficients β_q. The following patterns emerge: First, high-wage workers have lower unemployment risk. Based on the measure of unemployment I use, the likelihood of moving into unemployment is 50% higher for workers in the low bin. The second is that workers with the same wage, employed at a firm with different exposure to the GFC, have very similar probabilities of becoming unemployed.

Combined, these two findings imply that while labor-market adjustments in financially constrained firms disproportionately affect costly workers, they have a lower incidence of ending up unemployed as a result. As opposed to Mueller (2017) for U.S. data, I do not find that the pool of unemployed in Denmark shifted towards workers with previously high wages after the GFC.[14] The reason is that they are re-employed quickly.

Wage developments The data allows to estimate what labor market conditions the separated workers face once matched to a new firm. To do so, I replace the left-hand side of equation (4) with the growth rate of the wage in the new, relative to the old job. Note that the new job can be in *any* firm, including the public sector, as long as an hourly wage is reported. I take the log of the first oberved wage after a separation in 2008/09, and subtract the log of the wage in the separated job.

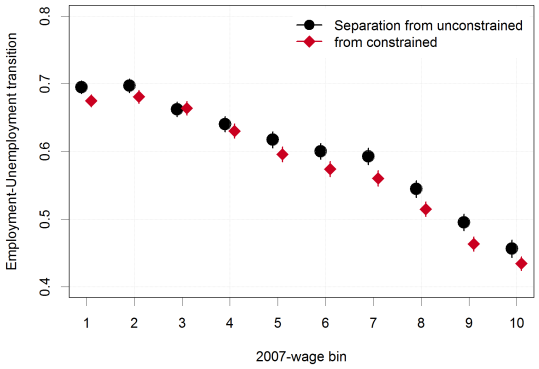
Figure 11(b) shows, first, that the between-jobs wage growth after separations during the Great Recession is negative for the 6 highest deciles of workers. Second, workers with previously high wages take considerably larger wage cuts once re-employed. The differences are large: Workers with the highest wages in 2007 take a 5-10% wage cut. Third, there is again no difference in wage growth across the financial position of previous employers.

The data does not allow to distinguish between voluntary and involuntary separations, and the findings presented above can indeed be interpreted as labor demand and labor supply adjustments. Barbosa et al. (2019) argue that workers with high human capital (in my application with high wages) sort themselves into jobs at firms with continued access to credit and therefore the ability to pay wages continuously. A purely supply-driven interpretation would imply, however, that this insurance is worth a premium of up to 10% of the wage. Especially in light of the stickiness of incumbent workers, a reduction of firm demand for workers with the highest wage is more preferable.

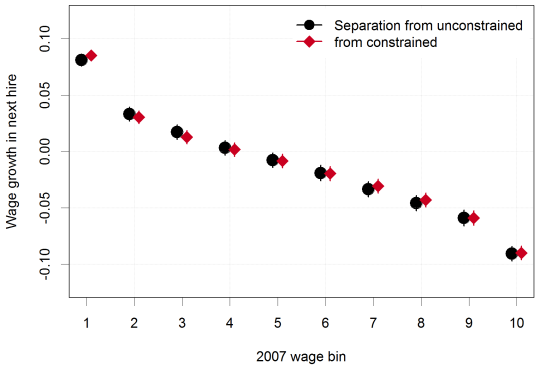
[14] Although, it should again be noted that my data is set up to track the *employed*, and that the pool of unemployed is measured rather imprecisely, given data limitations.

FIGURE 11: LABOR MARKET RE-ALLOCATION

(a) Transitions into unemployment



(b) Wage in next job



Note: Probability of observing an unemployment spell (panel a) and wage growth from current to next job (panel b) conditional on having a separation in 2008 or 2009, by pre-crisis wage bin and by financial position of the previous employer. The latter is defined as having loans from banks that are exposed to the liquidity shock in the banking sector of 2008.

Taken together, the firm-level results and the subsequent job market flows provide a rationale for large employment effects of financial shocks, followed by low wage growth for an extended period of time. Constrained firms reduce labor cost where it most effective: with the highest-paid employees. Low-wage workers are more likely to move into unemployment, while high-wage workers are re-employed quickly. Pries (2008) and Ravenna and Walsh (2012) have proposed channels for this effect to make recessions endogenously deeper: As the pool of unemployed deteriorates, firms have lower incentives to post vacancies. Firms prefer to hire workers with previously high wages, but pay them considerably less. As the economy recovers, lower-wage workers move out of unemployment and further depress aggregate wage growth.

6 Conclusions

My empirical analysis delivers four main findings: First, I use variation in the exposure of Danish banks to the Global Financial Crisis to show that liquidity shocks in the financial system are transmitted to credit supply at the firm level. Second, access to (both internal and external) liquidity plays a role in firms' ability to fund their working capital. Constrained firms retain cash flow predominantly by reducing employment, rather than the wage paid to each worker. At the same time, they build up liquidity buffers to insure themselves against future shocks. Third, I provide novel evidence of a margin to most effectively improve cash flow: Employment of the most costly workers is reduced disproportionately in constrained firms. I do not directly address the normative implications of this composition effect. However, the fact that the gradient in wage composition adjustments is driven by residualized wages rather than worker productivity could point to the fact that these adjustments could have cleansing effects (Baley et al., 2018). Fourth, I

show that this compositional adjustment is different for an alternative source of business cycles. In a local labor demand shock, the strongest decline is in employment for low-wage workers, while high-wage workers are almost unaffected.

Finally, I discuss and test implications for the cyclicality of employment and wages when workers re-allocate and wages adjust in a new job spell. As wages within job spells are sticky, the extensive margin of employment absorbs most of the need to shrink the outflow of cash. The previously highly paid workers find new work quickly, but take wage cuts relative to their previous job. Therefore, wage growth is low in constrained firms because of the described compositional shifts and in unconstrained because wages of new hires adjust downward. Low-wage workers spend more time in unemployment, depressing firms' incentive to hire and leading to slow recoveries. Once re-hired, the composition shift of the employed workforce once more depresses growth in the aggregate wage rate. My findings are therefore consistent with large drops of employment after financial shocks, and sluggish wage growth well after the labor market has stabilized.

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A Data appendix

A.1 Data sources and coverage

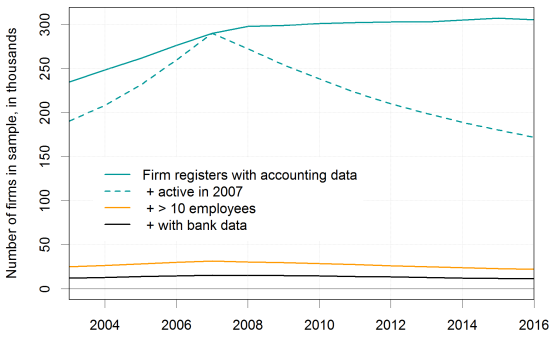
I compile detailed micro data from 10 different sources. This section describes the original data compiled and kindly made available by Danmarks Statistik. They are, for the most part, based on tax-relevant filings, and augmented by surveys on firm accounting statistics (FIRE), annual payrolls (LON) and financial statements of banks (URTEVIRK). Before describing the coverage and treatment of the data in more detail, Table A1 summarizes the data sources and main variables used.

On the individual side, the registers cover the universe of individuals with residence in Denmark, and the firm registers cover very closely the aggregate employment series in the country, which includes the large public sector. However, accounting data is only available for a subsample of firms; public sector, financial and agriculture are excluded altogether. More than half of employment (1.5 million individuals on average) are working at firms which are covered by the 200'000 firms for which accounting statistics are available (see green lines in Figure A1). The average firm size is therefore 7.5 employees. More importantly, the sample replicates the cyclical patterns in absolute terms, rather than relative. Employment in the whole economy falls by a little over 0.33 million (13%) during the Great Recession, the amount of jobs captured in the accounting statistics falls by 0.29 million (18%). This reflects the relative acyclicality of the unconvered firms.

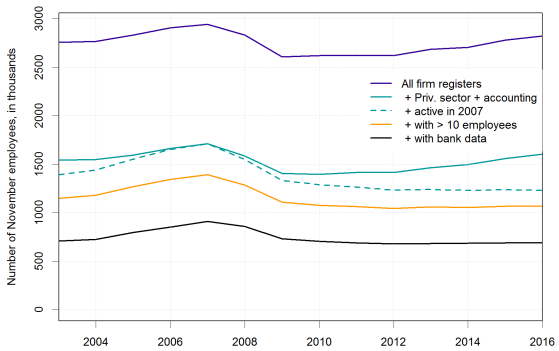
Dropping firms that consistently have less than 10 employees reduces the amount of unique firms by a factor 7 – from more than 200'000 in the average year to between 25'000 and 29'000 firms per year. This selects a constant share of private sector of employment of 80-82% (see orange line in figure A1), and is the baseline sample of firms analyzed.

FIGURE A1: SAMPLE COVERAGE

(a) Number of firms



(b) Employment



Note: Number of firms (panel a) and workers in November (panel b), compared across time and different sample selection criteria. The selected sample (in orange) only makes up a small fraction of the universe of firms, but a large share of private-sector employment and has the same cyclical properties. Furthermore, entry and exit rates are more stable, reducing extensive margin adjustment.

Table A1: Original data sources used

Register	Description	Identifier	Years used	Selected variables
Banks				
URTE-VIRK	Bank-borrower balances	bank, cvrnr	2003-2016	Year-end credit balance, interest
Finanstil-synet	Bank balance sheets	bank	2007	Total loans and deposits
Firms				
FIRM	Register of all firms	cvrnr	2003-2016	Year of entry and exit, November employment (HC)
FIRE	Firm-level accounting	cvrnr	2003-2016	Balance sheets, income statements, investment, aggregate employment over the course of the year (FTE)
KBI/KBB	Business tendency survey	cvrnr	2003-2016	Perceived financial constraints
Jobs/wages				
FIDA	Employer-employee link	cvrnr, pnr	1995-2013	Primary and secondary jobs in November each year
LON(N)	Annual wage statistics	cvrnr, pnr	1997-2016	Hourly wage, hours worked[1]
Individuals				
IDAP	Individuals	pnr	1990-2016	Income per calendar year, age, weeks of unemployment, years of employment experience
UDDA	Education	pnr	1990-2016	DISCED-15 code of highest completed education[2]
AKM	Occupations	pnr	1991-2016	DISCO code of main labor income, DISCO-08 as of 2010[3]

Registers are made available through and documented by Danmarks Statistisk's Danmarks Statistik's Forksningsservice. HC = head count, FTE = full-time equivalents. Identifiers: pnr is the personal registration number, cvrnr is the firm identifier. A firm can consist of of multiple establishments (arbnr).

[1] Definition of hours worked and hourly wage is subject to changes over time. They are described in more detail in section A.2

[2] DISCED-15 is the Danish education classification system aligned with the international ISCED 2011. It can be translated to eight levels from primary school to a doctoral degree as well as the standard years of schooling to complete.

[3] DISCO is the Danish application of the International Standard Classification of Occupations ISCO-88. As of 2010, the most recent version DISCO-08 (equivalent to ISCO-08) is used.

This sample has several appealing features: First, it preserves the boom and bust of private-sector employment: It explains 96% of the variance of nation-wide employment. Second, it reduces potential biases induces by firm entry and exit. While in the unrestricted sample, less than 60% of firms survive the decade after the Great Recession. The average annual exit rate of firms in the selected sample is 1.7%, (4.1% in 2009), mitigating concerns about the extensive margin of employment adjustment. Ultimately, only firms of a sufficient size consistently report wage data on their employees and allow to study the effects on workforce composition in a meaningful way.

35% of firms report their balance sheets throughout the entire sample period, the mean length of uninterrupted observations is 9.4 (out of 14) years. When accounting for firms entering and exiting the market, these numbers climb to 63% of firms and 12.2 years, respectively.

Observable variables include a detailed disposition of balance sheets, including liquid assets, financial securities in both sales and fixed assets, as well as tangible and intangible fixed assets. The sum of the latter two is defined as the firm's capital. Furthermore, liabilities are classified as short-(/long-)term financial debt based on whether their maturity is less (more) than one year, accounts payable to suppliers, as well as equity. The income statement also follows standard accounting principles, and apart from sales and expenses on raw materials, salaries and interest payments, taxes and depreciation, the distribution of profits, which emerges from the income statement, will be considered in the regression analysis because it too is a margin of adjustment when credit constraints are binding.

On the financial side, I merge firms to loans in the URTEVIRK register, which is a third-party reported snapshot of not securitized loans at lenders in Denmark. However, I restrict the lender side to 101 actual banks, which annual balance sheets to the financial supervisory authority (Finanstilsynet) and, if of sufficient size, monthly loans to the non-financial corporate sector in the Monetary and Financial Statistics to the Danish central bank.

46% of firm-years can be matched to a bank loan. This share increases with the size of the firm, but even for large corporations, the match rate stays below 90%. However, the firms that do match obtain the same dynamcis in terms of employment than the baseline firm sample (see black line in Figure A1)

Finally, section 3.2 of the paper uses the Business Tendency Surveys for the manufacturing and construction sectors linked to the balance sheets of 2'766 firms between 2003 and 2016.

A.2 Data treatment: Jobs and wages

The FIDA registers are annual snapshots of the labor market at the end of November, starting in 1997, include both primary and secondary jobs, and serve as the core dataset of the job-level analysis. This section describes the procedure merging and handling the data: First, multiple employer-employee links in the same year are collapsed to only one observations. Second, employees who never work at any of the firms described above are disregarded. This concerns 64% of individuals. Third, the dataset is merged to the individual-level registers described in the data source description, and observations of individuals younger than 25 or older than 60 are dropped. Fourth, information on job-level salary payments is added from the LON(N) registers.

Wages Prior to 2002, the hourly wage in the definition used post-2002 has to be imputed by by summing the has to be added manually, comprising of the "narrow "wage definition, pension contributions, and well as payments for holidays, sick leave and payments in kind, all divided by the registered work hours carried out.

Residualized wages In Section 4.2 of the paper, I residualize nominal wages following Abowd et al. (1999) on the subset of connected workers and firms. Practically, the two-way fixed effect regression performs can only identify worker and firm fixed effects if a worker has – between 1997 and 2016 – worked for at least two different firms, which in turn have employed at least two different workers. This is the case for 57.53% of worker-firm-years. For those observations, the log hourly wage is regressed on a set of explanatory variables using two-way fixed effects on worker i and firm j identifiers.

$$w_{i,t} = \alpha_i + \psi_{j(i,t)} + \Pi' \times Z_{i,t} + \omega_{i,t}$$

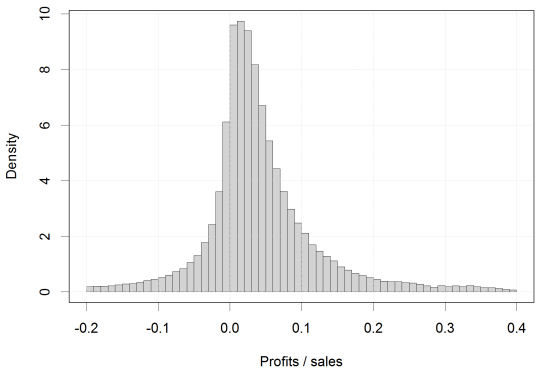
The vector of covariates Z includes the following variables: age and squared age, the expected years of schooling for the highest degree obtained, a fixed effect for the occupation, labor market experience since graduation, as well as tenure in the current job.

Unionization Labor unions play a central role in the Danish labor market, and more than 70% of Danish wage-earners are union members. Absent a national minimum wage or the like, unions and employers negotiate sector-specific collective agreements which cover non-members as well, but neither companies nor workers are legally required to comply. If union-negotiated wage agreements constitute a source of downward nominal wage rigidity, one would assume this effect to be stronger for workers with lower wages. Consequently, the wage stickiness would lead to more adjustments along the extensive margin, as indeed shown by Olsson (2020). This effect would work against findings presented in this paper.

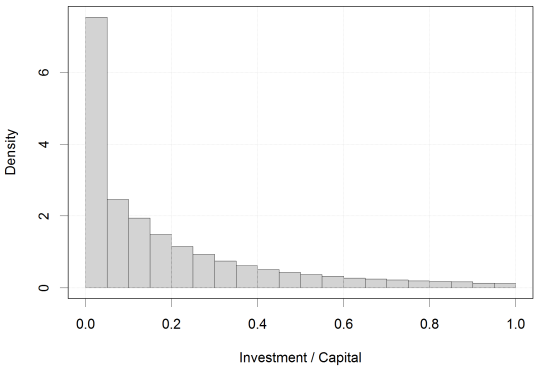
A.3 Descriptive statistics

FIGURE A2: DESCRIPTIVE DISTRIBUTIONS: FIRMS

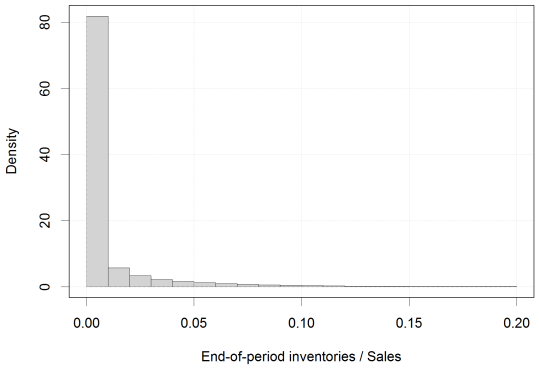
(a) Profit ratio



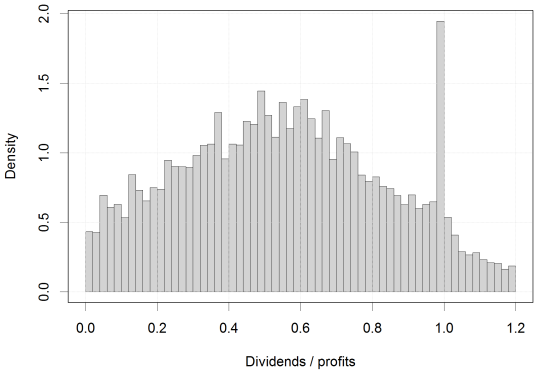
(b) Investment / lagged capital



(c) Inventories/sales



(d) Dividends/profit



Note: Histograms/cross-sectional distributions of key balance sheet variables used in the regressions.

Table A2: Sample: Descriptive statistics

Firms[1]	All	Bank $\mathbb{1}[LTD_{07}]_b$ Weak	Healthy	Internal liquidity ℓ_{07} Low	High
# observations	416,525	90,194	95,362	171,157	174,631
# firms	39,784	7,405	7,799	14,167	14,525
# NACE3 industries	239	208	206	200	209
Firm exit rate, mean (%)	2.1	1.3	1.3	1.9	1.6
Age, mean	16.93	19.19	18.20	15.00	18.59
Employment, median	11.78	14.08	13.70	14.02	11.31
–, mean	33.26	40.51	50.56	43.57	28.52
–, p90	50.74	62.14	75.29	71.05	42.07
–, mean, pre-GFC	35.02	51.56	52.20	45.82	28.45
–, mean, post-GFC	32.32	39.98	49.54	42.21	28.57
Liquidity ratio, median	1.65	1.48	1.38	1.06	2.35
Debt ratio, median	0.53	0.53	0.54	0.54	0.50
# firms linked to bank	27,314	7,398	7,787	10,465	10,467
# bank links p. firm, mean	1.19	1.24	1.22	1.22	1.17
Jobs[2]	All		p0-p20	p40-p60	p80-p100
# workers (thousand)	2,239		178.81	151.97	168.30
–, in sample firms (th.)	1,904		162.16	136.47	155.63
# jobs per worker, mean	1.99		2.31	2.27	2.30
Job spell length, mean	3.35		3.04	3.79	4.28
Annual separation rate (%)	26.71		32.00	24.39	20.16
–, of which EE (%)	46.11		43.38	49.25	61.13
Wage available (%)	68.39		76.74	81.21	82.65
Hourly wage (DKK), mean	270.53		187.87	225.73	406.51

[1] The firm sample considers all unique firm identifiers which over the cours of 2003-2016 report employing 10 or more employees at least once. Columns (2) and (3) describe the subsample of firms matched to a bank loan, and columns (4)-(5) split the sample by the liquidity ratio (cash over labor cost) in 2007.
[2] Unique employer-employee matches are defined as jobs, and are split up into distributional bins (upper, lower and medium quintile) of the 2007 wage distribution among the firms in the sample, which is the definition used in the main body of the paper.

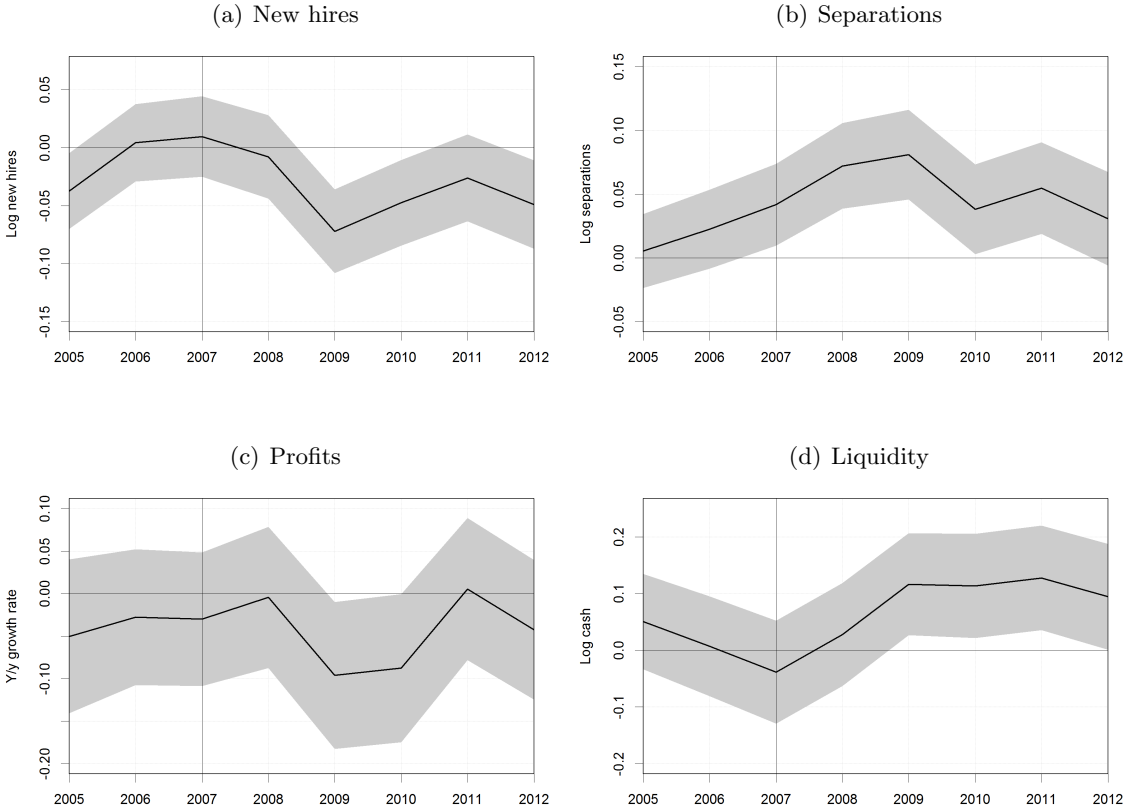
B Supporting empirical results and robustness checks

B.1 Further results and robustness on firm-level outcomes

B.1.1 Other firm-level outcomes

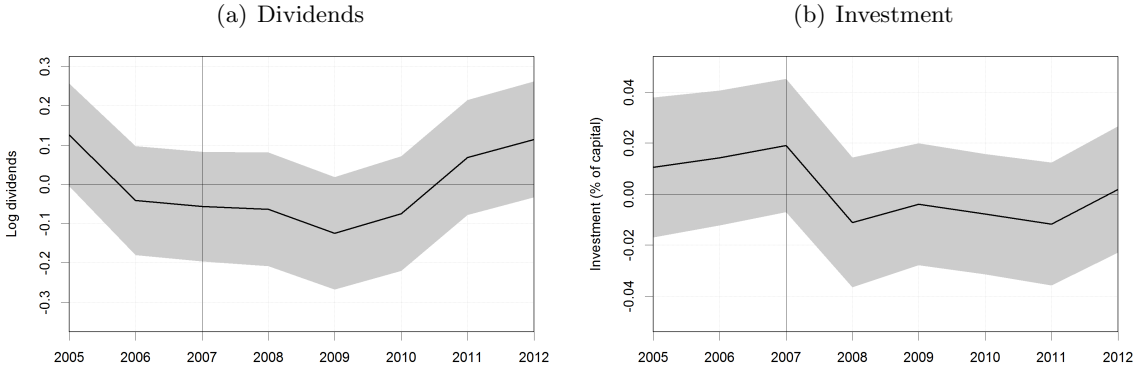
The following graphs complement Figure 6 by repeating the difference-in-difference regression with other firm-level variables. The treatment is defined as having a pre-crisis lending relationship with a bank that, in 2007, has a loan/deposit ratio larger than the median across banks, and is thus highly exposed to the money market freeze during the financial crisis.

Figure A3: DiD regression results: Other firm-level outcomes



Note: The black line represents difference-in-difference estimates of a negative credit supply shock, measured by the weighted loan/deposit ratio of a firms' banks in 2007. The left-hand side variables are the log of all new matches observed since November of the previous year (panel (a)) and the log of number of employees that were previously employed but no longer work at that firm (panel b). Panel (c)/(d) depict regression results using the symmetric growth rate of profits (where the highest and lowest 5% of the data are winsorized) and log liquid assets, respectively. The grey bands represent 95% confidence intervals of the point estimate. Standard errors are clustered at the firm level.

Figure A4: DiD regression results: Other firm-level outcomes



Note: The black line represents difference-in-difference estimates of a negative credit supply shock, measured by the weighted loan/deposit ratio of a firms' banks in 2007. The left-hand side variables are the log of dividends as well as the investment rate, defined as the amount of investment as a share of last period's tangible assets. The grey bands represent 95% confidence intervals of the point estimate. Standard errors are clustered at the firm level.

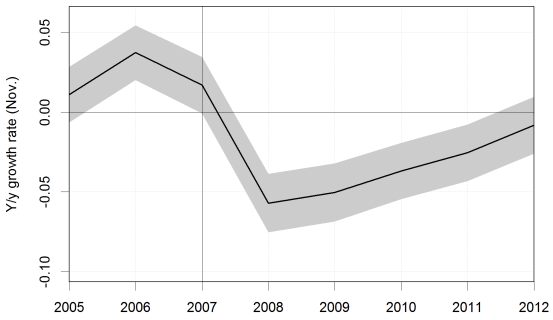
B.1.2 Firm-level outcomes by pre-crisis liquidity

In Figure A5, I show that the main results of the firm-level analysis are robust to replacing the treatment with the specification for internal liquidity used in the body of the paper: whether or not the liquidity ratio was above or below the median of firms in 2007.

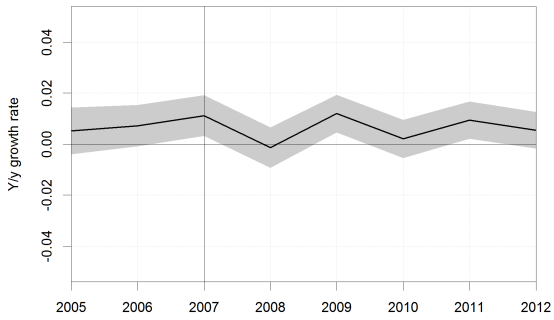
Furthermore, I want to highlight the non-linear nature of the liquidity-employment nexus. I group the firms by liquidity ratio in a base year into 10 equally-sized bins, sum employment over all firms in the bin, and calculate the growth rate of employment in subsequent years within that bin, relative to the base period (see Figure A6). Comparing outcomes in boom periods by looking at employment growth by 2005-liquidity shows that the gradient is flat, indicating that internal liquidity is of minor importance when credit constraints are slack. In crisis years, however, the relationship is strongly positive: Firms in the lowest five deciles of the 2007 liquidity ratio distribution have significantly worse employment outcomes than those with high liquidity buffers. They employ 35% fewer workers in 2009 compared to 2007, whereas firms with the highest liquidity ratios contract by only 20%. Note that this aggregate analysis does not account for the creation of and hiring by newly established firms. The elasticity between financial positions and firm growth is shown to be highly nonlinear over the business cycle.

Figure A5: DiD regression results: By 2007 liquidity ratio

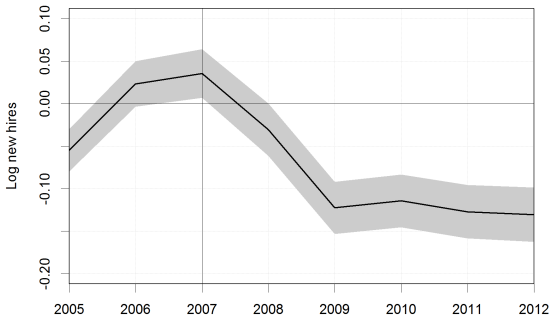
(a) Employment growth



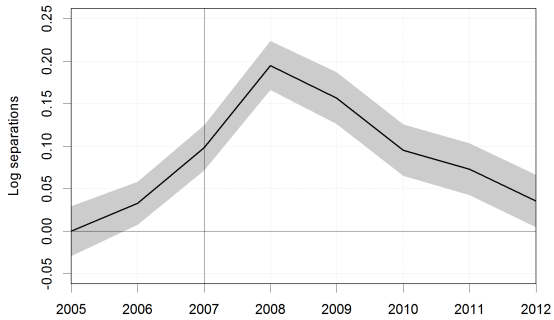
(b) Average nominal wage



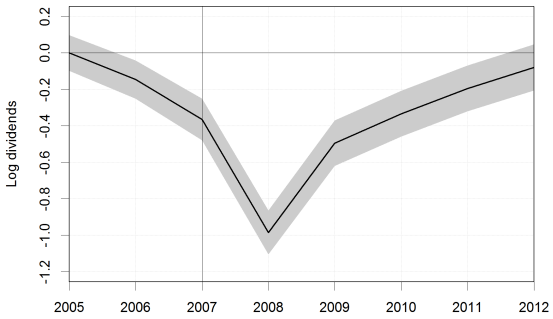
(c) New hires



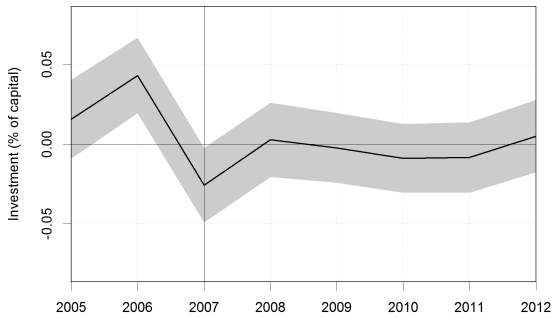
(d) Separations



(e) Dividends

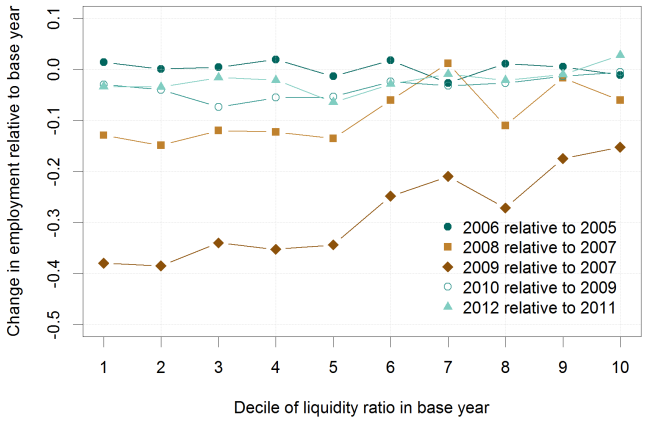


(f) Investment



Note: The black line represents difference-in-difference estimates where the treatment group consists of all firms with a ratio of liquidity to lagged fixed cost below the median of their 3-digit NACE industry. The left-hand side variables are the annual symmetric growth rate of employment (since November of the previous year, panel (a)) and the average annual wage paid at the firm in the respective year (panel b). Further included are the log of all new matches observed since November of the previous year (panel (c)) and the log of number of employees that were previously employed but no longer work at that firm (panel d). Panel (e) depicts regression results using the log of dividends as the dependent variable and panel (f) is for investment. The grey bands represent 95% confidence intervals of the point estimate. Standard errors are clustered at the firm level.

FIGURE A6: LIQUIDITY AND EMPLOYMENT GROWTH: A NON-LINEAR RELATIONSHIP



Note: Growth rates of employment relative to a base year in all firms within a decile of liquidity ratio in the base year. The used liquidity ratio is the stock of cash as a share of previous labor cost.