# Dynamics of Corporate Credit Markets, Employment and Wages: Evidence from Colombia

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**Abstract**

This paper examines the impact of changes in corporate credit supply on employment and wages outside of financial-crisis episodes. We construct a rich annual employee–employer–credit-bank database using Colombian administrative data from the period 2008–2018 and estimate corporate credit-supply shocks using firm and bank fixed effects. These estimates provide new evidence on three empirical facts: In response to a positive credit-supply shock, (i) firms increase their investment but do not change their average employment or wages; (ii) wages decline in the bottom half of the wage distribution while increasing at the top of the distribution; and (iii) firms with more liquid assets increase employment. We develop a small-open-economy model where the effect of a credit-supply shock is consistent with the empirical facts. In the model, two opposing mechanisms are key to explaining the results: capital–low-skill substitutability and firm-specific liquidity constraints to finance labor. These competing forces explain why average wages and employment do not change in response to credit-supply shocks while low-skilled wages decline. We use the model to study how permanent reductions in the banking intermediation premium influence firm-level responses to credit-supply shocks. Relative to the baseline model, we show a positive short-term impact on employment and wages and a negative long-term effect.

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# 1 Introduction

The large rise in unemployment during the global financial crisis made clear the link between firms' access to credit and labor markets. An extensive literature has developed documenting these links and investigating the theoretical channels by which credit and labor markets interact (Mian and Sufi, 2014; Chodorow-Reich, 2014; Huber, 2018; Berton et al., 2018; Giroud and Mueller, 2017; Duygan-Bump et al., 2015; Baghai et al., 2018; Calvo et al., 2012). Financial crises, however, are extreme and rare events (Reinhart and Rogoff, 2008) for banks, firms, and workers. In this paper, we shift the focus from crises to study how access to credit affects employment and wages when neither banks or firms are facing extraordinary conditions. To answer this question, it is necessary to track the links between banks, firms, and workers. We create a novel administrative data set from Colombia between 2008 and 2018 that provides these links. We find that average employment and wages do not respond to an exogenous increase in credit supply. Instead, workers in the bottom of the distribution lose with these credit-supply expansions. Moreover, we find that the heterogeneous effect on workers is more pronounced in firms with low liquidity. We develop a model of financial frictions and labor markets to study the mechanisms and the aggregate effects.

The directions of the effects on employment and wage of a change in access to corporate credit are not obvious. An expansion of corporate credit supply creates investment opportunities. With these opportunities, a firm that does not face internal liquidity restrictions should expand in scale by increasing both its capital stock and its labor demand. When a firm faces liquidity constraints, however, trade-offs arise. Should the firm allocate funds to increase investment or should the firm increase payments to labor? Which types of labor should the firm hire in this circumstance? If labor and capital are complements, then both may rise, but if some types of labor and capital are substitutes, then an increase in investment may cause demand for those types of labor to decline. As a result, we can observe wages of some workers going down and labor demand only expanding for some firms.

We use administrative data of large firms in Colombia from three different sources.[1] First, we use financial reports from the Colombian government agency in charge of overseeing corporations, *Superintendencia de Sociedades*. Second, we use employer–employee data from the *PILA* system, which is equivalent to the Social Security Administration in the United States. Third, we use credit data from the Colombian government agency in charge of overseeing financial institutions, *Superintendencia Financiera*. In addition, we use publicly available bank financial reports. We develop a merging algorithm using the firm's and individual's national identifiers to link the data.

[1] Firms with either sales or assets of more than 20,000 times the legal minimum wage—around 4.11 USD million—are obligated to report. The average minimum wage in Colombia during the period was 205.8 USD, using the Dec 2018 COP/USD exchange rate of 3,208.263.

Our empirical strategy proceeds as follows. First, we estimate firm-level idiosyncratic credit-supply shocks. We use data from the credit reports on firm–bank relationships and credit growth. The shocks capture differences in credit supply relative to the median bank. We closely follow the identification strategy from Amiti and Weinstein (2018), Jiménez et al. (2019), and Khwaja and Mian (2008). We aggregate the shocks at the firm level and use each firm's financial reports and employer–employee data to document three facts. First, using Jordà's (2005) local projections, we estimate that a one-standard-deviation positive credit-supply shock increases firms' bank borrowing and gross investment by 2.3% and 1.8%, respectively. We find that employment and average wages do not have a statistically significant response to a positive credit-supply shock. This result is in contrast to the existing literature that finds that employment substantially decreases during large credit contractions (Chodorow-Reich, 2014; Huber, 2018).

Second, we study heterogeneous effects across the wage distribution. We estimate quantile regressions at the worker level (Firpo et al., 2007) to estimate the effect on each decile of wages. We find a negative and significant effect on wages below the median one and two years after the shock. The lowest decile declines 0.4% in response to a one-standard-deviation positive credit-supply shock. This means that a credit expansion increases wage dispersion during normal times, with wages at the bottom end of the distribution falling. This result highlights the relevance of tracking the links from the banks to firms to workers.

Third, we study heterogeneous responses at the firm level. In particular, consistent with Gilchrist et al. (2017), we find firm responses depend on their internal liquidity. Regardless of the liquidity position, all firms increase their capital stock by around 2% in response to a one-standard-deviation positive credit-supply shock. However, labor demand and working capital have heterogeneous responses. High-liquidity firms not only increase their capital stock, but increase employment. In contrast, low-liquidity firms reduce their working capital by 1.3%. The lowest wages fall by 10% (5%) in low-liquidity (high-liquidity) firms.

We interpret our results as follows. A positive credit-supply shock creates an investment opportunity. Firms facing no liquidity constraint are able to expand in scale. Labor demand will change differentially for all types of workers, but it increases overall, thus the increase in employment. However, firms with insufficient internal resources to simultaneously increase capital and hire more of all types of workers will reduce demand for those workers that are well substituted by capital, typically low-wage workers. Employment and wages for these low-wage workers may decline. Therefore, these two forces, capital–skill substitutability and internal liquidity constraints, allow us to rationalize why we do not observe changes in average wages or employment. These facts are in line with the capital–skill-substitutability literature (Vom Lehn, 2020; Lafortune et al., 2019; Alvarez-Cuadrado et al., 2018; Acemoglu and Autor, 2011). Moreover, the liquidity-channel result reconciles our aggregate-employment findings with the existing literature on financial crises. We can interpret financial crises as circumstances in which firms are extremely liquidity constrained. As a result, employment decreases.[2]

We develop a model to illustrate how internal liquidity constraints to finance labor interact with differences in the substitutability of capital and labor. The model is a real small open economy with working-capital constraints, a liquid asset, banks, two types of labor (skilled and unskilled), and a frictional labor market. Our model closely follows models of working-capital constraints (Neumeyer and Perri, 2005; Quadrini, 2011). We use a simple functional form of the production function (Vom Lehn, 2020), in which output is produced by skilled labor and routine jobs. Routine jobs can be done using capital or unskilled labor.

We calibrate the model to our data and find that a positive credit-supply shock reduces low-skilled wages over a three year horizon in the presence of both mechanisms—liquidity constraints and a capital–low-skill substitutability production structure. The short-term effect on high-skilled wages depends on two key parameters: the elasticity of labor supply and the magnitude of the working-capital effect. The long-term effect is always positive. The effect on average wages and employment depends on the elasticity of substitution between capital and labor, and on the importance of capital to production.

To isolate the effect of each mechanism, we repeat our simulations turning off one channel at a time. We find that low-income wages slightly decline in the absence of liquidity constraints, while high-income wages increase relative to those offered by constrained firms. When the production structure only uses one type of labor, we find a small reduction in wages one period after the shock and a significant increase later. Thus, the presence of both mechanisms is necessary to describe the observed in the data. Liquidity constraints and capital–low-skill substitutability force low-skilled wages permanently lower and induce more demand for high-skilled workers. When both mechanisms are in place together, the effects on average wages and employment are weakly positive.

Finally, we use our model to ask how reductions in the intermediation premium—the difference between the rate paid on bank deposits and the borrowing rate—influence firms' response to credit-supply shocks. We find that low-income workers do not lose as much as in the baseline model when the intermediation premium decreases by 20%. In particular, we find that one year after a positive credit-supply shock, low-skilled wages are 5% higher compared to our baseline model. In contrast, high-skilled wages are 8% lower. As a result, employment and average wages are lower compared to the original calibration. In this experiment, we reduce the importance of the banking shock as an investment opportunity. We allow credit-supply shocks to move around a permanent lower cost. When the economy as

[2] In the additional results in the appendices, we find that when we restrict our sample to large shocks—more than one standard deviation—we find that positive credit-supply shocks have a positive and significant effects on employment.

a whole faces lower borrowing interest rates firms do not respond as much to credit-supply expansions. Therefore, the trade-off between expanding capital and increasing labor demand is less apparent. The new change in access to capital is not large enough for low-liquidity firms to choose between capital and labor. Our results suggest that expanding credit has limited ability to produce changes in average wages and employment, but it can potentially increase labor-income inequality.

### 1.1 Related literature

Our paper contributes to three branches of the literature. First, our paper is related to the extensive literature that studies financial shocks and labor markets (Berton et al., 2018; Huber, 2018; Popov and Rocholl, 2018; Chodorow-Reich, 2014). The seminal work of Chodorow-Reich (2014) demonstrates the use of instrumental variables: During the global financial crisis, employment in firms with banking relationships with more affected banks was disproportionately hurt. Huber (2018) and Popov and Rocholl (2018) find a similar effect in Germany, while Berton et al. (2018) not only confirm this result for Italy, but show heterogeneous effects according to education level and type of contract. We contribute to this literature in two key dimensions. First, we study the response of employment and wages to an increase in credit supply during normal times. This approach allows us to understand other mechanisms at the firm level that are relevant in understanding the credit–labor-market relationship. In this sense, our second contribution shows heterogeneous effects across different types of workers. Only workers at the bottom of the distribution lose with a positive credit-supply shock. In this sense, the nature of the shock matters to establish how credit affects labor markets.

Second, our study is related to the literature on financial shocks and firm dynamics (Amiti and Weinstein, 2018; Jiménez et al., 2019; Gilchrist et al., 2017; Kim, 2018). Methodologically, our paper closely follows Amiti and Weinstein (2018),[3] identifying credit-supply shocks through bank–firm relationships using bank and firm fixed effects. Our paper is related to the research that studies price-setting decisions and margins of adjustment from credit-supply shocks (Gilchrist et al., 2017; Kim, 2018). It is similar to this literature in two ways. We study the effects of credit shocks and liquidity on the price of labor. We also highlight the importance of the liquidity channel. In this sense, our contributions to this literature are twofold. First, we bring a new data set in which we are able to link banks, firms, and workers. This data allows us to further understand the effects of a credit-supply shock beyond those at the aggregate level. Second, to our knowledge, ours is the first paper that studies how corporate credit-supply shocks affect wages from the firm perspective. We

[3]Previous work from Khwaja and Mian (2008) and a more recent paper from Jiménez et al. (2019) use a similar methodology.

find that capital–skill substitutability and liquidity constraints are key to understanding our results. Our paper underscores the importance of credit shocks for firm choices not just during crises, but also during normal times.

Third, we contribute to the literature that studies financial frictions in small open economies (Neumeyer and Perri, 2005; Quadrini, 2011; Leyva and Urrutia, 2020). From this perspective, we can establish our contribution in two aspects. First, in terms of the empirics, we differ from this literature because we provide micro-level evidence of how financial frictions affect employment and wages. We inform our model with rich cross-sectional evidence that highlights the importance of the liquidity channel. Second, in terms of the model, we add three dimensions to the standard approach of a small open economy with working capital: a bank, a liquid asset, and the capital–skill substitutability channel. In particular, we add how banking shocks that abstract from aggregate large fluctuations have aggregate effects in small open economies (Morelli et al., 2021; Bianchi and Mendoza, 2020; Sosa-Padilla, 2018; Martin and Philippon, 2017; Fernández and Gulan, 2015; Fernández-Villaverde et al., 2011; Mendoza, 2010).

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 shows the results of the credit-shock estimation. Section 4 describes the empirical strategy and the main results of the paper. Section 5 describes the model and the simulations. Section 6 concludes.

## 2 Data

In this section, we explain the sources of the data and the linking process between three administrative-data sources. Our banking data comes from the Colombian government agency in charge of overseeing financial institutions, *Superintendencia Financiera*. Colombian banks and credit institutions are obligated to report the balance of all their credit operations every quarter (*Formato 341*). This information allows us to track the total amount of lending from a bank $b$ to a firm $f$ from the first period of the loan until its maturity. We restrict our data to credit issued between January 2008 and December 2018. We keep credit lines with maturity greater than 1 day and less than 90 years, with complete history,[4] with total initial debt above 10,000 COP (around 3 USD), and with interest rate below the legal maximum rate of the period (33.51% in 2017-1). In addition, we restrict our sample to banks with more than three years of data and to banks with more than five relationships. Then, to aggregate the data at the firm level, we keep the debt stock for each bank–firm in the fourth quarter. See data Appendix A.1 for more details about the data-

[4] The first observation corresponds to the initial date. The last observation corresponds to final credit date.

organization process. Our final sample has 138,683 firms and 16 banks.[5] We also use banks' publicly available monthly financial statements from the *Superintendencia Financiera*. See Appendix A.1 for more details.

At the firm level, we use financial reports and their corresponding appendices from the *Superintendencia de Sociedades*, the government agency in charge of overseeing corporations. Firms with either annual sales or assets of more than 20,000 times the legal monthly minimum wage (about 4.11 million USD) are obligated to report.[6] We use the annual reports from 2008–2015[7] and restrict our sample to firms that report positive sales, assets, liabilities, and equity, verifying that in all reports the basic accounting identity holds. See, Appendix A.4 for details about the data-organization process.

A contribution of our paper is the ability to link banks' corporate credit reports with firms' financial statements and workers' employment histories. That is, we link credit reports—*Formato 341*—with financial reports—*Super-Sociedades*—and with social security payment reports—*PILA*. Colombia uses a unique official identifier for each corporation and for each individual. The corporations' unique identifier is called *NIT*—*número único de identificación tributaria*. This number identifies banks and firms in our data. We can think of the *NIT* as the equivalent to the United States' EIN—*employer identification number*. The individuals' unique identifier is called *cédula*, and it is comparable to the United States' SSN—*Social security number*. To link the credit reports and the financial statements we use the banks' and firms' *NIT*s. The link between the financial reports and the workers' employment history is more challenging. As we mentioned before, the financial reports identify firms using *NIT*s. The social security payment reports, however, use a different identification system. This database does not use *NIT*s and *cédulas* to identify firms and workers. We developed a merging algorithm where we create a one-to-one mapping between the national firm identifiers *NIT* and the *PILA* identifiers. See Appendix A.5 for details about the merging algorithm.

After identifying the link between *NITs* and *PILA* firm identifiers, we construct the employer–employee data set. We use data from the firms' monthly social security payment reports—*PILA*—between 2008 and 2018, restricting the sample to the firms we identified. Each formal employer in Colombia reports every month the social security payments to

[5] AvVillas, Banco Caja Social BCSC, Banco de Bogotá, Banco GNB Sudameris, Bancolombia, Bancoomeva, Banco Popular, Banco WWB, BBVA Colombia, CitiBank, Copatria Red Multibanca, Davivienda, Helm, Banco de Occidente.

[6] The average minimum wage in Colombia during the period was \$205.8 USD, using the Dec 2018 COP/USD of 3,208.263.

[7] We restrict our financial reports to 2015 because Columbian firms started a transition in this year between the domestic accounting system—PUC—and the international standards—NIIF. Therefore, reports from the subsequent years have some structural differences and incompatibilities, being the first in which this transition has been realized in different stages. In years 2016–2018, some firms submitted their reports in the PUC system and others submitted in the NIIF system.

**Table 1:** Summary Statistics

| | **Mean** | **Std. Dev** | **P95** | **P5** | $N$ |
|---|---|---|---|---|---|
| | | | **Firms** | | |
| Employment | 121 | 526 | 429 | 3 | 10,835 |
| Leverage | 0.38 | 5.41 | 0.73 | 0.02 | 10,835 |
| Equity to Assets | 3.62 | 86.16 | 8.28 | 1.17 | 10,835 |
| Capital | 16.24 | 222.11 | 42.79 | 0.15 | 10,835 |
| Sales | 10.96 | 141.50 | 32.69 | 0.22 | 10,835 |
| Banking Shock | 0.05 | 0.13 | 0.27 | −0.12 | 10,835 |
| | | | **Workers** | | |
| Wage | 542.96 | 625.46 | 1,683.68 | 166.71 | 3,321,640 |
| Age | 34.83 | 10.32 | 54.00 | 21.00 | 3,321,640 |
| Male | 0.59 | 0.49 | 1.00 | 0.00 | 3,321,640 |

**Note:** $N$ is the total number of firms or workers. Employment: Average number of workers per year.

each worker based on their basic monthly wage. We drop observations that have a daily wage below half of the minimum daily wage. We construct the daily wage as the monthly wage divided by the number of reported days.[8] We move from monthly to annual frequency using only information for December each year. With this method, we observe year-to-year changes that coincide with the date of the financial reports.[9] To address seasonality concerns, we verify our results by aggregating the data using information from all months. We generate monthly averages, following Alvarez et al. (2018). See Appendix A.6 for more details about the organization process. We deflate each variable using the December 2018 average monthly Colombian CPI and the December 2018 COP/USD exchange rate.

Our final sample contains 10,835 firms and 3,321,640 workers. Our sample corresponds to large financial firms in Colombia,[10] not only in terms of sales, but in number of employees and average wages. Table 1 shows that, on average, a firm in our sample has more than 100 employees, sales of almost 11 million USD per year, and a leverage to total assets of 38%. Our sample is comparable in terms of employment and leverage to firms in COMPUSTAT in the United States. In terms of wages, on average, our firms pay lower wages than U.S. firms, but higher wages compared to the Colombian market. The average wage in our sample is \$542.96 dollars per month, about twice the average minimum wage of the sample period.[11]

[8]In Colombia, in contrast to the United States, workers cannot be hired hourly. Instead, they can have full-time contracts—48 hours per week—or part-time contracts—24 hours per week.

[9]We use December because that is when firms submit their financial reports.

[10]We exclude firms in the public sector, electricity, and water supply. We include firms in real estate and the financial sector that issue no credit and that are not publicly traded as they are not in the bank sample.

[11]Using our own computations and aggregate data from the National Department of Statistics, *DANE*, the average wage in Colombia is slightly higher than the minimum wage.

## 3 Identifying Shocks to Credit Supply

To identify shocks to credit supply at the firm level, we closely follow (Amiti and Weinstein, 2018, hereafter AW). This framework, identifies credit-supply shocks as the firms' common change in borrowing from a particular bank. In other words, we measure the firm–bank pair variation in borrowing explained by changes in credit supply. This methodology is a generalization of a common identification strategy in the literature of financial shocks (Jiménez et al., 2019; Mian and Sufi, 2014; Iyer et al., 2014; Schnabl, 2012; Khwaja and Mian, 2008). The AW methodology differs from the rest of the literature in the sense that it does not take a stand on the nature of the credit-supply shock. Instead, it relies on the structure of the banking system to identify shocks using firm and bank fixed effects. To be concrete, suppose a particular firm, $f$, borrows some quantity $d_{fb}$ from a bank $b$. In each period $t$, debt can change either due to a shift in firm $f$'s borrowing from all banks ($\alpha_{ft}$), a shift in bank $b$'s lending to all firms ($\beta_{bt}$), or forces idiosyncratic to firm $f$ and bank $b$ ($\epsilon_{fbt}$). This situation is summarized in equation (1)

$$\Delta d_{fbt} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{1}$$

AW show that expressing changes in debt of firm $f$ from bank $b$ as percentage changes and estimating equation (1) with weighted least squares (WLS) provides a consistent estimator of $\beta_{bt}$. Also, the estimation procedure allows for creation and termination of credit relationships,[12] and it is possible to aggregate at the firm level keeping a reasonable economic interpretation of the shocks.

To allow for the creation and destruction of bank–firm relationships and to give an economic interpretation, we renormalize equation (1) by adding an intercept $c$ and leaving as omitted categories the first bank and the first firm:

$$\Delta d_{fbt} = c_t + \tilde{\alpha_{ft}} + \tilde{\beta_{bt}} + \epsilon_{fbt}, \tag{2}$$

where $\tilde{\alpha}_{ft}$ captures the change in borrowing coming from firm $f$ compared to the change in borrowing of the omitted firm: $\tilde{\alpha}_{ft} = \alpha_{ft} - \alpha_{\text{omitted}t}$. Similarly, $\tilde{\beta}_{bt}$ captures the change in lending of bank $b$ compared to the change in lending of the omitted bank: $\tilde{\beta}_{bt} = \beta_{bt} - \beta_{\text{omitted}t}$. Notice that $c_t$ acts as time fixed effects and captures all the common change in debt in period $t$. The intercept captures the business-cycle fluctuations. We use as omitted category the median firm and bank shocks from equation (1) following Amiti and Weinstein (2018).

We estimate equation (2) using WLS. Then, we use the estimated bank fixed-effect

[12] Our data, is characterized for bank–firm relationships that are not very persistent over time when compared, for example, with Chodorow-Reich (2014).

coefficients and aggregate them at the firm level to define a credit-supply shock.[13] We use as weights the importance of each bank $b$ in firm's $f$ debt in period $t-1$:

$$\theta_{fbt} = \frac{d_{fbt-1}}{\sum_b d_{fbt-1}}. \tag{3}$$

We define a credit-supply shock as

$$\textit{Supply Shock}_{ft} = \sum_b \theta_{fbt-1}\hat{\hat{\beta}}_{bt}. \tag{4}$$

We interpret a change in loan supply to firm $f$ relative to the average change in credit supply as a credit-supply shock, idiosyncratic changes in the credit supply. This method of estimating credit-supply shocks has two particular features. First, it identifies idiosyncratic shocks. In this sense, it differs from the literature that studies the firm-level effects of aggregate credit-supply shocks (Chodorow-Reich, 2014; Huber, 2018). Second, it requires a particular structure of the banking system. Given that this method relies on fixed effects, we need sufficient overlap between banks and firms, a set of banks and firms that are connected to each other. If a bank lends to only one firm, it is not possible to identify if changes in debt are coming from the bank or from the firm. An equivalent situation arises if all firms borrow from all banks. We want to capture relative differences in credit supply. We also need granularity of banks. This means that we need a large set of banks, in which the presence of all banks and firms is nonnegligible, but no one bank can be crucial to the existence of the market. We require granularity to argue that changes in one particular bank can have aggregate effects. If all banks have a negligible impact on the market, the failure of one bank does not affect the equilibrium outcomes. Figure 1 illustrates both of the conditions required for identification. Panel A shows that two of the banks—Bancolombia and Banco de Bogotá—control 40% of the credit portfolio. This situation guarantees the relevance of some of the banks in the market without allowing any one bank to be completely dominant. Similarly, Panel B shows that on average, firms have more than one banking relationship over time. We highlight that the credit reports' structure offers an ideal setting to estimate these idiosyncratic credit-supply shocks.

We estimate equation (2) from the credit data and validate our results with the banks' cross section using the banks' publicly available financial reports merged with our estimates of the credit-supply shocks. See Appendix A.2 for the data-organization process.[14]

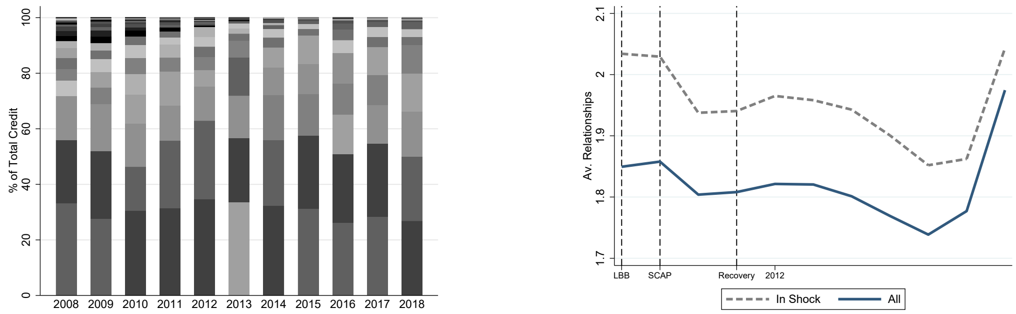
We first verify that the $\hat{\hat{\beta}}_{bt}$ are positively correlated with the percentage change of commercial credit reported from the banks' balance sheets. We estimate $\hat{\hat{\beta}}_{bt}$ using $\Delta d_{fbt}$

[13] AW show a moment condition, $\Delta d_{ft} = \hat{c}_t + \hat{\hat{\alpha}}_{ft} + \sum_b \theta_{fbt-1}\hat{\hat{\beta}}_{bt}$ (equation (8) in AW), that captures the total change in old and new borrowing of firm $f$ that exactly matches the firm loan growth rates.

[14] Table 8 in the appendices shows that all firms and banks are connected.

**Figure 1:** Identifying Assumptions of the Banking Shock

**(a)** Credit Concentration **(b)** Number of Banking Relationships




**Note:** Data source: Formato 341. Panel A shows the share of total corporate credit for each bank in our sample. We compute corporate credit as total credit issued by each bank to all firms in the first quarter each year. Panel B shows the total number of banking relationships per firm. The solid line shows the average number of relationships in the entire sample. The dotted line shows the average number of relationships of firms with more than four consecutive periods in the sample.

from the credit reports and expect our estimated $\hat{\hat{\beta}}_{bt}$ to be correlated with the percentage change in lending, $\Delta d_{bt}$, from the banks' balance sheets but different from one because the change in lending is an equilibrium object. The first column of Table 2 shows this result. We regress $\hat{\hat{\beta}}_{bt}$ on the percentage change of commercial credit and on time fixed effects using OLS. As expected, the coefficient is less than one and statistically significant at $p < .01$.

In addition, we expect $\hat{\hat{\beta}}_{bt}$ to be related to measures of bank health. Our shock captures the cross-sectional changes in credit supply relative to the median bank. That is, we expect healthier banks to experience positive credit-supply shocks compared to unhealthier banks.

**Table 2:** The Credit-Supply Shock Is Correlated With Healthier Banks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $\hat{\beta}_{bt}$ | | | |
| $\Delta$ log Comm. credit | 0.27*** | | | |
| | (0.08) | | | |
| Dividends dummy | | 0.34** | | |
| | | (0.06) | | |
| CASA | | | 0.36*** | |
| | | | (0.14) | |
| Capital to liabilities | | | | −0.43 *** |
| | | | | (0.22) |
| Time FE | Yes | Yes | Yes | Yes |
| $N$ | 145 | 145 | 145 | 145 |

**Note:** Each column estimates $\hat{\beta_{bt}} = \eta_1 + \eta_2 y_{bt} + \alpha_t + \epsilon_{bt}$, where $y_{bt}$ is a bank-level outcome (Change in credit, CASA ratio, Dividends dummy, Capital adequacy), and $\alpha_t$ are time fixed effects. Robust standard errors in parentheses clustered at the bank level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Even though our methodology does not take a stand on the interpretation or economic nature of the credit-supply shock, we can imagine situations that increase credit supply. Examples include bank marketing activities that increase the number of deposits and extra returns in investments other than corporate credit. In this sense, we use as measures of banking-health dividend payments, checking and savings deposits as shares of deposits (CASA), and liabilities to capital as a measure of capital adequacy. We use dividend payments instead of market-to-book ratio[15] because most banks in our sample are not publicly traded. To address the limitation of our sample, we follow Khwaja and Mian (2008) and use the CASA ratio as a measure of liquidity. Banks with more checking and savings deposits have liquid funds that do not require high interest payments. As a final measure, we consider the capital adequacy of the bank measured as total liabilities divided by the bank's registered capital. We expect a negative correlation between our measure of capital adequacy and the credit-supply shock. Columns 2–4 of Table 2 show the OLS estimated coefficients of regressing $\hat{\beta}_{bt}$ on each of the banking health measures and time fixed effects. Columns 2 and 3 show paying dividends and deposits are positively and statistically correlated with the credit-supply shock. Column 4 shows that the credit-supply shock is negatively correlated with highly indebted banks.

We also validate our shock in the time-series dimension. By construction, our estimates of the credit supply abstract from aggregate fluctuations. Equation (1) captures the year-by-year cross-sectional variation of borrowing coming from the banks. Thus, the common components of the business cycles are absorbed. When we normalize by the median shock per year, instead of an arbitrary bank, we measure change in credit coming from the bank that is different from the aggregate component. However, because we estimate the shock year by year, we might expect some anticipation of the shocks or some aggregate effects transmitted through the banks. In Table 3, we estimate an AR(1) model of the credit-supply shock, and add as control the cyclical component of GDP using an HP filter on impact, one period before and one period forward. These results suggest two important conclusions. First, the shocks have a small but statistically significant autoregressive component. That is, some bank characteristics that affect credit supply persist over time. Second, the credit-supply shock is not correlated with the business cycle. This is important because, as we said, our goal is to capture changes of credit supply that are different from aggregate components or financial crises.[16]

To summarize, we estimate a credit-supply shock that captures the change in corporate credit coming from the banks. This variation captures the idea that healthier banks expand

[15] Amiti and Weinstein (2011) use market-to-book ratio as the main measure of banking health.

[16] Given some persistence of the shock, we verify our firm- and worker-level results using only the residuals of the estimates in Column 1 of Table 3. Our results are robust to this change. However, we prefer the original specification to maintain the economic interpretation of the estimated coefficients.

**Table 3:** The Credit-Supply Shock Is Uncorrelated With the Business Cycle

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | $\hat{\beta}_{bt}$ | | |
| $\hat{\beta}_{bt-1}$ | 0.36*** | 0.36*** | 0.36*** | 0.37*** |
| | (0.12) | (0.12) | (0.12) | (0.12) |
| Cyclical component GDP | | 0.39 | | |
| | | (0.87) | | |
| Cyclical component $\text{GDP}_{t-1}$ | | | −0.02 | |
| | | | (0.91) | |
| Cyclical component $\text{GDP}_{t+1}$ | | | | 1.24 |
| | | | | (0.93) |
| Cons | 0.00 | −0.01 | 0.00 | −0.02 |
| | (0.02) | (0.01) | (0.02) | (0.02) |
| $N$ | 137 | 137 | 137 | 123 |

**Note:** Each column estimates $\hat{\beta_{bt}} = \eta_1 + \rho\hat{\beta_{bt-1}} + \eta_2 y_{bt} + \epsilon_{bt}$, where $y_{bt}$ is the cyclical component of GDP using the HP filter with smoothing parameter $\lambda = 400$. Column 2 uses on impact GDP, Column 3 uses lagged GDP, and Column 4 uses forward GDP. Robust standard errors in parentheses. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

their credit supply independently of what happens in the aggregate economy. In the next section, we use this measure to study how corporate credit affects workers.

# 4 The Effect of Credit Shocks on Employment and Wages

## 4.1 Methodology

In this section, we establish three facts describing the effect of an exogenous increase in credit supply on the labor market. First, we explore the effect on investment, employment, and wages at the firm level. Second, we turn to worker-level regressions to see how worker characteristics affect wages' the response to a corporate credit-supply shock. Third, we exploit firm-level heterogeneity to understand how firm-specific characteristics affect the response of labor demand to a positive credit-supply shock.

At the firm level, we estimate

$$\log Y_{ft+h} - \log Y_{ft-1} = \beta_{0h} + \beta_h \, \textit{Supply Shock}_{ft} + X_{ft-1}\Gamma_h + \alpha_{jth} + \alpha_{fh} + \epsilon_{fth}, \tag{5}$$

where $Y_{ft+h}$ is a firm-level outcome of interest (investment, employment, or wages), $\alpha_{jth}$ are sector–time fixed effects, $\alpha_f$ are firm effects, and $X_{ft-1}$ is a set of firm-level controls. Our coefficient of interest, $\beta_h$, measures the cumulative change in $Y_{ft+h}$ to a one-unit increase in the credit supply relative to the median $h$ years after the shock, a Jordá projection (Jordà, 2005). Because we only have firm-level controls until 2015, we study the effect up to three years after the shock given the number of years in our data, $h = \{0, 1, 2, 3\}$. We use our estimates of the credit-supply shock in equation (4) as our measure of the credit-supply shock.[17] Our controls include firm size in terms of sales and number of locations, liquid assets to total assets,[18] and demeaned leverage. Our controls are in line with Ottonello and Winberry (2020), Amiti and Weinstein (2018), and Gilchrist et al. (2017). We cluster the standard errors at the firm and date levels and use this specification to study the aggregate effects and the firm-level heterogeneity.

To explore the effects of a corporate credit-supply shock on workers, we estimate the effect of a positive credit-supply shock on each decile of income. To keep our analysis comparable with the firm-level results, we first estimate the effect of a positive credit-supply shock on wage growth of worker $i$ as

$$\begin{aligned}\log(w_{ift+h}) - \log(w_{ift-1}) &= \beta_h \, \textit{Supply Shock}_{ft} \\ &+ \beta_{hd} \, \textit{Supply Shock}_{ft} \times \textit{decile}_{it-1} + X_{ift-1}\Gamma_h + \alpha_{fth} + \alpha_{ih} + \epsilon_{ifth}, \quad (6)\end{aligned}$$

where, $\textit{decile}_{it-1}$ is the workers' position in the wage distribution one period before the shock. $\alpha_{fth}$ are firm–time fixed effects, $\alpha_i$ are worker fixed effects, and $X_{ift-1}$ is a set of controls. Our coefficient of interest, $\beta_h + \beta_{ht}$, measures the cumulative change in $w_{ift+h}$ after a one-unit increase in the credit-supply $h$ years after the shock for each of the wage deciles. We use as additional controls the worker's age and age squared as to proxy experience. We cluster the standard errors at the firm and time levels.

To estimate the overall effect on the distribution of wages, we estimate the effect of a credit-supply shock on each decile $p\left(\log(w_{ift+h})\right)$ using unconditional quantile regressions (Firpo et al., 2007; Rios-Avila, 2020):

$$p\left(\log(w_{ift+h})\right) = \beta_0 + \beta_s \, \textit{Supply Shock}_{ft} + X_{ift-1}\Gamma + \alpha_{fth} + \alpha_i + \epsilon_{ifth}. \quad (7)$$

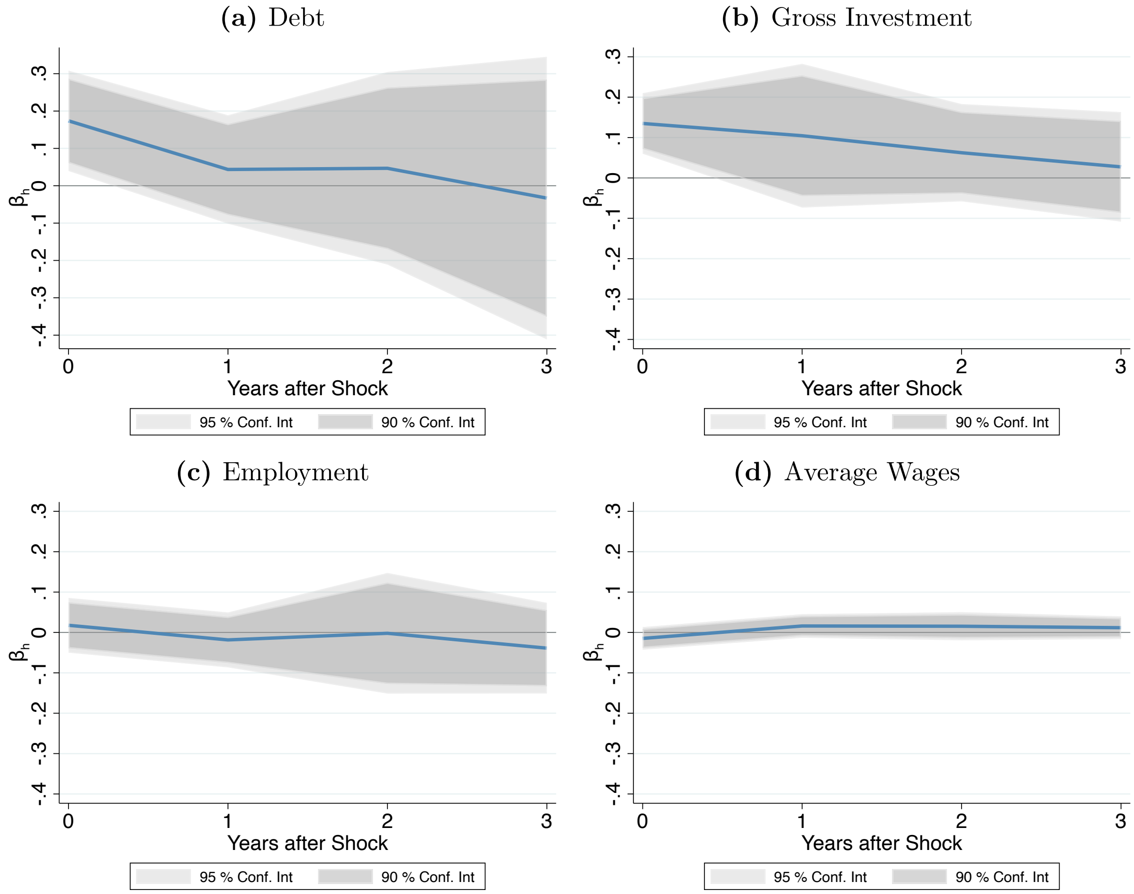
To keep our analysis comparable with the Jordá projections at the firm level, we study the effect of a shock in $t$ on the distribution of wages one, two, and three years after the shock: $h = \{0, 1, 2, 3\}$.

## 4.2 How credit supply affects investment, employment, and wages

First, we establish a positive effect of the credit-supply shock on banking debt. We measure a firm's banking debt as the total debt from all domestic banks using data from the firms'

[17] Since we use estimated regressors we compute our standard errors using a bootstrap.
[18] By liquid assets, we mean cash and short-term investments.

**Figure 2:** Impulse Response Functions to a Positive Credit-Supply Shock




**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on banking debt using equation (5). We measure banking debt from the financial reports as total debt from domestic banks. Panel **(b)** shows the effect on capital stock. Panel **(c)** shows the estimated effect on employment using equation (5). We measure employment as the total number of workers. Panel **(d)** shows the effect on the average wage. We interpret the change in capital as gross investment. We report the 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

financial reports. Figure 2a shows that the effect of a positive credit-supply shock on banking debt is significant on impact and goes to zero after that. Table 10 in the appendices shows the effect without firm-level controls. We highlight two points. First, this fact offers proof of concept for our credit-supply shock. Recall that we use data from credit reports to estimate changes in credit availability. A positive change in banking debt from the balance-sheet perspective implies more credit availability results in an actual change in borrowing. Second, the effect is temporary, but large. A firm that receives a positive credit-supply shock of one standard deviation (0.13), increases its debt position with the banks by 2.34% ($0.18 \times 0.13$). This effect is sizable compared to the average banking-debt growth rate, $-6\%$.[19]

[19] Table 9 in the appendices summarizes the one-year growth rates of the main variables of interest.

Figure 2b shows the effect on gross investment. We find that a positive credit-supply shock causes gross investment to increase on impact.[20] We interpret this as follows: When banks expand corporate credit, this translates into one period of borrowing. Firms use these new funds to finance investment projects to increase their capital stock. All of the new resources are used in the same period.[21] The size is again quite large. On average, the firms in our sample have decreased their capital stock 3% per year, and the effect of a one-standard-deviation shock is 1.8% (Tables 9 and **??** in the appendices). The effect on debt is smaller than the effect on the capital stock. The average firm receiving a one-standard deviation credit-supply shock increases capital stock by 0.29 million USD and debt by 0.15 million USD. This implies that firm raise funds from other resources, like cash.

We now turn to the effects of the credit-supply shock on labor market outcomes. We do not find a significant effect on employment or average wages. Figures 2c and 2d show the impulse response functions for employment and wages, respectively. From the graphs, we can not only conclude that the effect is not statistically significant, but its magnitude is also small. This result is quite surprising compared with previous findings on employment changes during financial crises. In particular, Chodorow-Reich (2014) and Huber (2018) find that after the global financial crisis, employment declined for firms that had relationships with more affected banks. To reconcile our results with theirs findings, we repeat our estimates for employment only allowing for large shocks. We define a large shock as a credit-supply shock to a firm that is one standard deviation above or below the median shock in a particular year. Our goal with this exercise is to try to capture the closest scenario to a financial crisis, a period with a large volatility of credit supply. Figure 16 in the appendices shows a positive and significant effect on employment on impact. This, highlights the importance of understanding the effects of credit supply on employment and wages outside financial-crisis episodes.

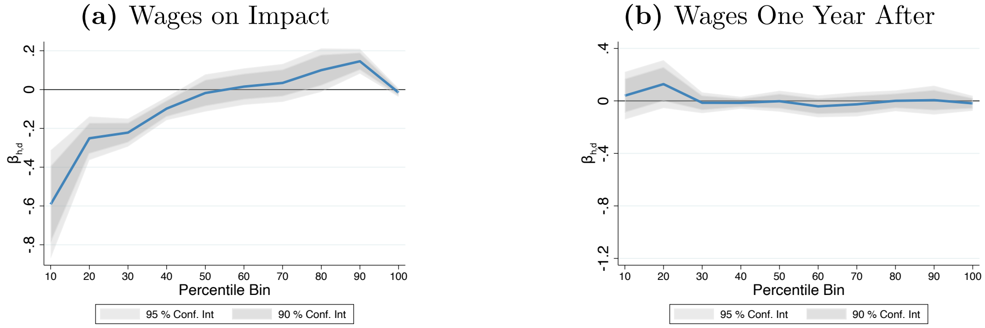
### 4.3 Uneven effect across types of workers

We exploit worker-level variation to estimate the impact of corporate credit-supply shocks on the distribution of workers or distribution of wages across workers. First, we study the effect on the growth rate of wages by decile, and then we study the level effect on the distribution of wages. To estimate the effect on wage growth, as described in equation (6), we classify each worker in a wage decile. The first decile of income includes workers with

[20] Measured as change in the physical capital.

[21] This result differs from Amiti and Weinstein (2018), who finds a positive credit-supply shock leads on average to an investment reduction for firms who rely on other sources of financing than loans. As the loan-to-assets ratio increases, the effect of a positive credit-supply shock becomes negative. One way to reconcile our results with Amiti and Weinstein (2018) comes from the composition of the sample. In their sample, the firms are publicly traded and use the capital market as a financing substitute. In our sample, most of our firms are unlisted. Therefore, our result is in line with the positive result for firms relying heavily on debt.

**Figure 3:** A Positive Credit-Supply Shock Reduces Wages in the Bottom Half of the Wage Distribution While Increasing Wages at the Top of the Distribution




**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on each decile bin using equation (6) for $h = 0$. Each point on the horizontal axis represent a decile of income from the lowest to the highest. For example, 10 represents workers in the 0 to 10 percentile of income. Panel **(b)** estimates the same value for $h = 1$. Each regression has 6,150,523 observations for $h = 0$, 2,976,639 for $h = 1$. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

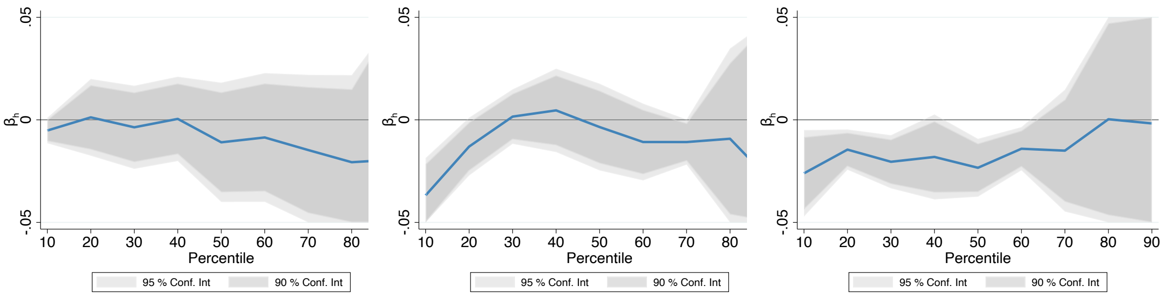
the lowest wages, while the tenth decile represents the top of the wage distribution. The coefficient of interest is the sum of the average effect and the interaction term between the shock and each decile. We interpret the result as the total effect on each wage decile.

Figure 3a shows the effect on impact while Figure 3b shows the effect one year after the shock. The horizontal axis shows each of the wage bins. For example, 10 represents workers in the 0–10 percentile, 20 is the group between 10 and 20, and so on. The vertical axis shows the estimated coefficient of the total effect of a positive credit-supply shock in the wage growth rate. On impact, we see a significant decline in wages below the median relative to wages on the top of the distribution. Similarly, wages on the ninth decile relatively increase relative to the mean. Wages of workers on the bottom of the distribution that receive a positive credit-supply shock of one standard deviation, decline by 7.8%. However, wages of workers on the ninth decile that receive an equivalent shock experience a wage growth of 2%. To put these numbers in context, the average growth rate of wages is 1.5%. This means that those at the top continue growing at a similar rate after the shock, but workers on the bottom receive less wages. The effect on the growth rate stops one year after the shock.

We show a temporary effect on the growth rate of wages. Now, we turn our attention to not the effect on each of the workers, but on the level of income: the cutoff values of each decile of income. Here, we seek to understand the effect of a credit-supply shock on the distribution. To do so, we estimate equation 6. Figure 4 establishes one of the paper's main empirical results. This time, the horizontal axis again shows each decile of income. The vertical axis shows the estimated coefficients for each decile's change in value. This exercise is important because we initially compared changes in wages of each of the groups of workers. Now, we study how the distribution changed. This allows for a recomposition

**Figure 4:** A Positive Credit-Supply Shock Reduces the Value of the Wage Deciles on the Bottom Half of the Distribution

**(a)** Wages on Impact **(b)** Wages One Year After **(c)** Wages Two Years After




**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on each income decile using equation (7) for $h = 0$. Panel **(b)** estimates it for $h = 1$ and Panel **(c)** for $h = 2$. The horizontal axis shows the wage deciles, and the vertical axis shows the change in each decile's cutoff value. Each regression has 6,150,523 observations for $h = 0$, 2,976,639 for $h = 1$, and 1,879,977 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

of each decile. The result shows a lasting negative effect on below-median wages one and two years after the shock. This means that a one-time shock has a negative and temporary effect on the growth rate of wages but has a more permanent effect on the overall wage distribution. Figures 4b and 4c show that there is a negative effect on low-income wages. In particular, the effect on the lowest decile is negative and statistically different from zero with 95% confidence one year after the positive credit-supply shock. Moreover, the effect extends to the bottom half of the distribution two years after the shock. This means that the lowest decile declines 0.65% due to a one-standard-deviation positive credit-supply shock to the workers' firm. Wages below the median decrease 0.26% two years after the shock.[22]

We interpret a credit-supply shock's positive effect on the capital and negative effect on the lower half of the wage distribution as evidence of capital–skill substitutability. Considerable research has shown the substitutability of capital and routine workers in developed countries (Vom Lehn, 2020; Lafortune et al., 2019; Alvarez-Cuadrado et al., 2018; Acemoglu and Autor, 2011).[23] In this sense, a credit-supply shock generates an investment opportunity, and, in taking it, firms reduce labor demand for those workers capital substitutes.

[22]To our knowledge, we are the first to estimate the heterogeneous effect of a credit-supply shock on wage distribution. Moser et al. (2021), closest paper to ours, have data on German workers, but they estimate the credit-supply shock coming from an aggregate monetary policy shock. In the paper, they ask how aggregate credit-supply shocks can shape within- and between-firm wage inequality. They find that the introduction of negative monetary policy rates increases (decreases) within-firm (between-firm) inequality. We differ from them in two dimensions. First, our shock is not an aggregate shock. Instead we capture banks' idiosyncratic changes to credit supply. That is, we abstract from the business cycle. Second, we do not study within- and between-firm inequality. Our decile estimates capture the effect on the overall distribution of wages.

[23]Although this literature has focused on the job–skill polarization in developed economies (see Acemoglu and Autor (2011) for an extensive review), Medina and Posso (2018) find suggestive evidence that this is also a characteristic of the Colombian labor market.

### 4.4 Uneven effect across firms: Liquidity constraints

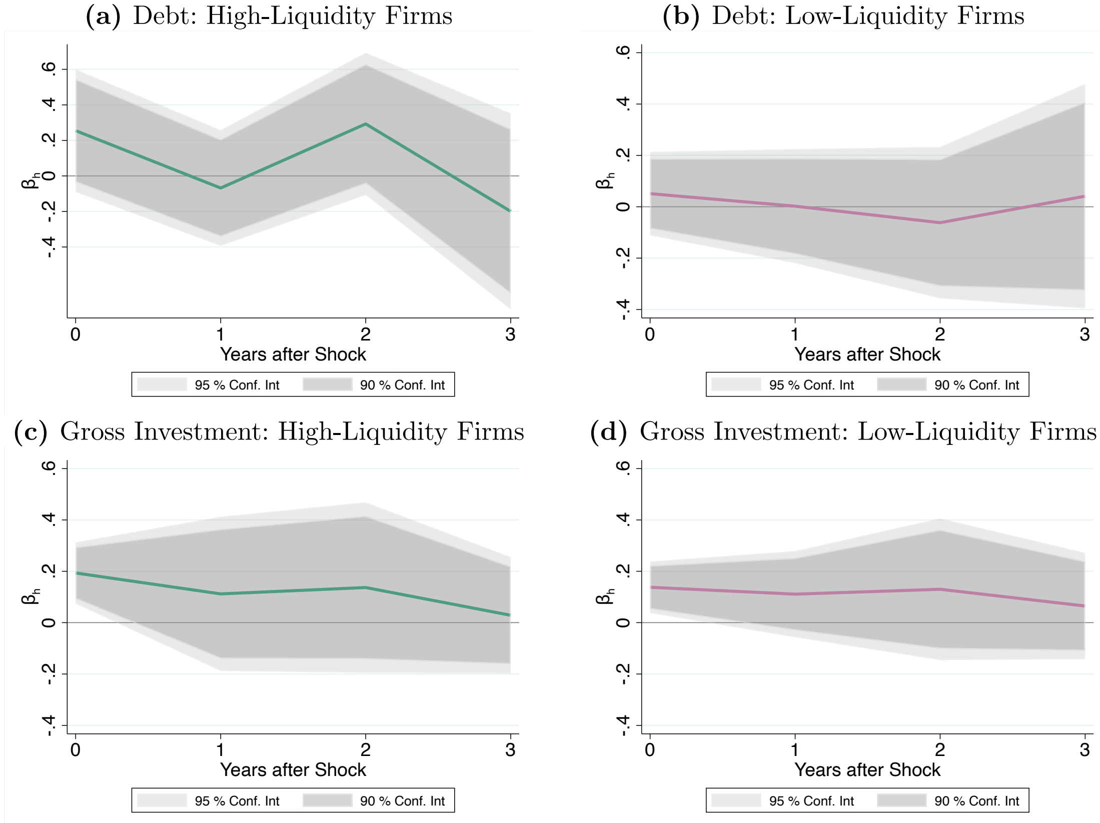
So, a positive credit-supply shock creates a physical-capital investment opportunity and simultaneously drives the bottom half of the wage distribution down. However, if these firms face an investment opportunity, why do they not expand in scale? Why is demand only changing for some workers? One potential explanation is the role played by liquidity. Gilchrist et al. (2017), for example, find that the liquidity channel is important to understanding how firms respond to external financial shocks. To preserve the ability to finance all current obligations, instead of expanding in scale, firms could choose to substitute some types of workers when they increase their capital stock. In this section, we study firms' heterogeneous responses to a positive credit-supply shock based on their level of liquidity.

We split our sample between high- and low-liquidity firms. The former has an above-average ratio of cash and short-term investments to assets. Figure 5 compares the effects on debt and gross investment between high- and low-liquidity firms. We do not observe heterogeneity in terms of debt and investment. We interpret this result as evidence that a positive credit-supply shock creates a similar investment opportunity for all firm types.

In the presence of working capital constraints financed with liquid funds and a production function where capital and labor are complements—neoclassical production function—we should expect that firms with more cash holdings—less financially constrained—could increase of their labor demand more than financially constrained firms. The first two panels of Figure 6 compare the effect on employment between high- and low-liquidity firms. The effect of a positive credit-supply shock is positive and statistically significant for high-liquidity firms. The point estimate for low-liquidity firms is negative and not significant. This suggests that one potential channel to explain our results is the presence of internal working capital constraints to finance labor. In the seminal working-capital-constraints literature, firms finance labor with external financing (Quadrini, 2011; Neumeyer and Perri, 2005). Our evidence suggests that firms use external debt financing to invest. This new investment is only accompanied by higher labor demand if the firm has enough internal resources to finance an expansion in scale. Otherwise, labor demand seems to decrease.

Figure 7 compares the effect on working capital between high- and low-liquidity firms. We measure working capital as the ratio of short-term assets to short-term liabilities. This measure compares the amount of liquid funds with the current obligations. With a positive credit-supply shock, low-liquidity firms reduce their working capital on impact and it remains low a year after the shock. In contrast, the effect on working capital for high-liquidity firms is positive and statistically significant one and two years after the shock. This suggests that the new investment opportunity creates a trade-off for firms with low liquidity: to take the investment opportunity they need to reduce their working capital, leading to a potential decrease in labor demand. High-liquidity firms do not face a trade-off and can expand in

**Figure 5:** Impulse Response Functions to a Positive Credit-Supply Shock on Debt and Gross Investment of Firms With Different Levels of Liquidity



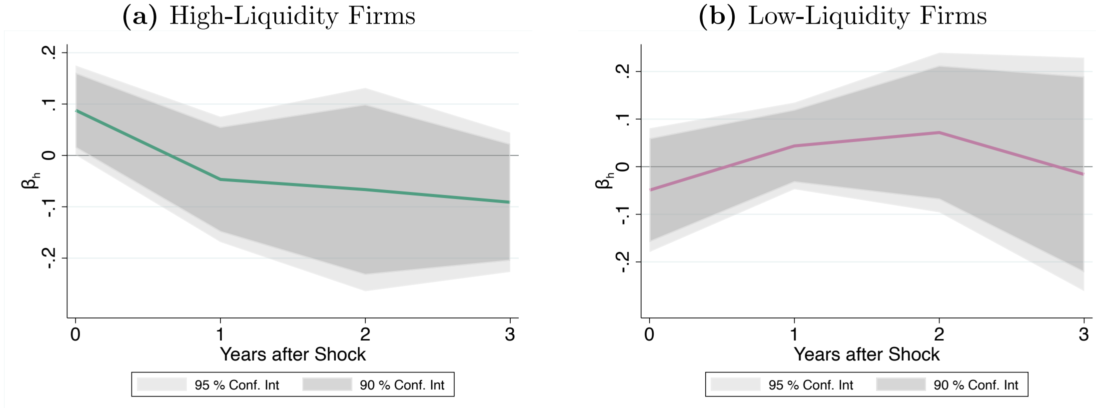

**Note:** Panels **(a)** and **(c)** show the estimated effect of a positive credit-supply shock on banking debt and gross investment using equation (5) for high-liquidity firms. Panels **(b)** and **(d)** show the estimated effect on banking debt and gross investment using equation (5) for low-liquidity firms. A high-liquidity firm has an above-average ratio of cash and show-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

scale. This expansion in scale generates more flow of funds for the firm. Thus, their working capital increases two years after the shock.

Finally we, show the effect on wages. We repeat our exercise and estimate the effect on wage growth using equation (6). Figure 8 shows the effect on wage growth at impact. Panel 8a shows the effect for high-liquidity firms, while panel 8b shows the same for low-liquidity firms. As expected, the negative effect on the bottom half of the distribution is more pronounced for low-liquidity firms. We interpret this result as evidence of the trade-off between increasing the capital stock and increasing labor in the presence of liquidity constraints. When capital is a substitute for some types of labor, the firm might increase the capital stock but reduce demand for those workers who capital substitutes. As a result we observe wages of some workers going down, and labor demand only expanding for some firms. The magnitude of the effect is significant. In high-liquidity firms, wages in the bottom of the dis-

**Figure 6:** Impulse Response Functions to a Positive Credit-Supply Shock for Employment of Firms With Different Levels of Liquidity

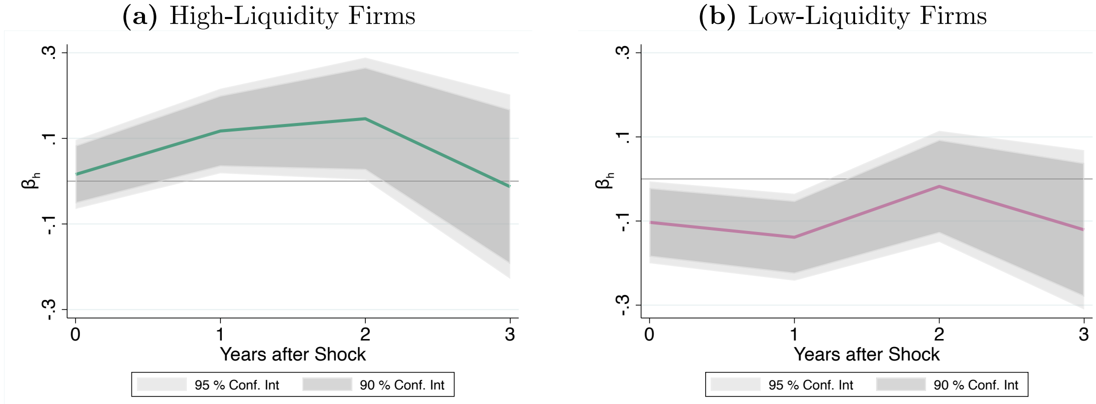
**(a)** High-Liquidity Firms **(b)** Low-Liquidity Firms




**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on employment using equation (5) for high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. A high-liquidity firm is a firm with an above-average ratio of cash and short-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

**Figure 7:** Impulse Response Functions to a Positive Credit-Supply Shock for Working Capital of Firms With Different Levels of Liquidity

**(a)** High-Liquidity Firms **(b)** Low-Liquidity Firms



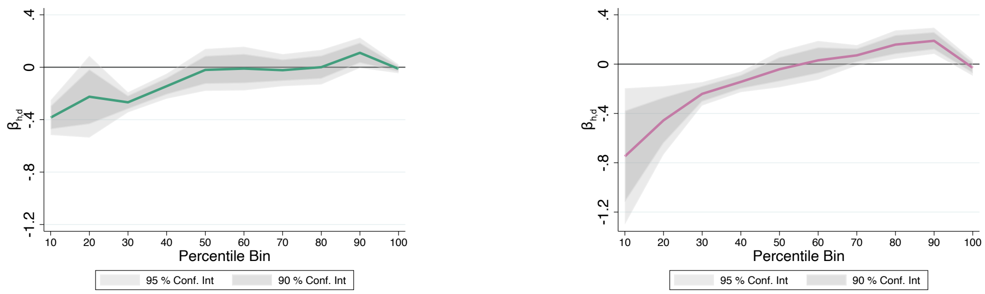

**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on working capital using equation (5) for high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. We measure working capital as the current-assets-to-current-liabilities ratio. A high-liquidity firm has an above-average ratio of cash and short-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

tribution decrease 5.3% after a one-standard-deviation shock, whereas low-liquidity firms' wages fall by 10%. This means that low-income workers in low-liquidity firms disproportionately lose with a positive credit-supply shock compared with the average worker and with the equivalent worker in a high-liquidity firm.

In this section, we documented three facts on the effect of positive idiosyncratic credit shocks. First, we find that firms increase investment but the effect on employment and wages

**Figure 8:** Heterogeneous Response on Impact to a Positive Credit-Supply Shock for Workers' Wages From Firms With Different Levels of Liquidity

**(a)** High-Liquidity Firms **(b)** Low-Liquidity Firms




**Note:** Panel **(a)** shows the estimated effect of a positive credit-supply shock on wages in income bins using equation (6) for $h = 0$ in high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

is small and insignificant. Second, we show that wages in the bottom half of the distribution decline. We interpret this result as evidence of capital–low-skill substitutability. Third, we provide evidence about one potential mechanism to explain why firms, when facing new investment decisions, increase their capital stock and low-income wages decline. We find evidence that the firm's internal financial constraints matter for how firms respond to a positive credit-supply shock. Firms with highly liquid asset holdings are more responsive to the shock and expand in scale. Firms with illiquid asset holdings reduce their working capital in a response to a positive credit-supply shock and if anything, reduce their labor demand. In the following section, we develop a model to rationalize how the interaction of these two mechanisms could explain our main findings.

# 5 Model

We construct a model consistent with the data. The model captures the positive effect of credit expansions on debt and investment as well as the heterogeneous impact on different types of workers and across different types of firms.

To capture these differences, and to keep the model simple, we develop a real small-open-economy model with working capital constraints by introducing banks, a liquid asset, two types of labor (skilled and unskilled), and frictional labor markets.[24] The role of the banks is that of a pass-through financial intermediary, where the presence of an intermediation premium generates a gap between the deposit rate and the borrowing rate. We define the credit-supply shock as variations to the banks' intermediation premium. The labor market is divided in two separate markets, one for skilled workers and another for unskilled workers.

[24] The search block follows Shimer (2010).

Workers search for jobs every period and bargain wages with the firms. We capture the workers' heterogeneity in terms of capital–low-skill substitutability. The firms produce using capital and labor, borrow from the bank to finance investment, and save in terms of a liquid asset to finance working capital. Households own the firms and the banks and supply labor.

In the model, time is discrete. The only source of uncertainty in the model comes from changes to the intermediation premium—the credit-supply shock. An aggregate state $s_t$ vector is governed by a Markov process with transition probability $\pi_s(s'|s)$, where $s$ and $s'$ are elements of the common state space $\mathbf{S}$. We start by describing the role of the household and the bank. Then, we describe the firms' environment to highlight how the interaction of the two types of labor with the working capital financed with the liquid asset generates opposing forces on employment and wages. After setting the firms' problem, we define the wage-bargaining process.

## 5.1 Household

The representative household is composed by many infinitely lived individuals of two types, skilled z and unskilled u, where each type has measure 1. Every period, the household chooses consumption $c(s)$, and savings $d(s)^h$ to maximize utility. To simplify notation, we suppress the aggregate state $s$ in the rest of the text when describing the elements of the model, but all outcomes are a function of this state. Every period, each household member $i_n \in [0, 1]$ is employed $l_n$ or unemployed $u_n$, where $n = \{\mathrm{z}, \mathrm{u}\}$. If employed, the worker earns a wage $w_n$. If unemployed the individual receives no income. The evolution of employment is determined by the workers' flow into and out of jobs. Employed workers in period $t$ become unemployed next period with exogenous probability $\rho_n$. Unemployed individuals in $t$ find jobs next period with probability $p(\theta)$, where $\theta_n$ is the market tightness in each labor market. The market tightness is the relationship between available vacancies and unemployment.[25] The household owns the bank and the firms, and receives dividends $\pi^{\mathrm{B}}$ and $\pi^{\mathrm{F}}$ correspondingly.

The household's recursive problem is

$$V_H(s, d^h, l_{\mathrm{u}}, l_{\mathrm{z}}) = \max_{c,d^h} U(c, l_{\mathrm{u}}, l_{\mathrm{z}}) + \beta \mathbb{E} V_H(s', d'^h, l'_{\mathrm{u}}, l'_{\mathrm{z}})$$

subject to

$$c + d^h = w_{\mathrm{u}} l_{\mathrm{u}} + w_{\mathrm{z}} l_{\mathrm{z}} + \frac{1}{M(s'|s)} d'^h + \pi^{\mathrm{F}} + \pi^{\mathrm{B}}$$

$$l'_n = (1 - \rho_n)\, l_n + p(\theta_n)\, u_n, \;\; n = \{\mathrm{z}, \mathrm{u}\}.$$

[25] We describe the search problem later in section 5.4.

The household receives utility for consumption and disutility for working as follows.[26]

$$U(c, l_{\mathrm{u}}, l_{\mathrm{z}}) = \frac{c^{1-\sigma}}{1-\sigma} - \phi\frac{l_{\mathrm{u}}^{\nu}}{\nu} - \phi\frac{l_{\mathrm{z}}^{\nu}}{\nu},\ \nu > 1,\ \phi > 0$$

From the household first-order conditions, we define the stochastic discount factor as

$$M(s'|s) = \beta E\frac{u_1(c', l'_{\mathrm{u}}, l'_{\mathrm{z}})}{u_1(c, l_{\mathrm{u}}, l_{\mathrm{z}})}.$$

## 5.2 Banks

The banks are owned by the household and pay dividends $\pi^{\mathrm{B}}$ every period. Banks take deposits $m$ from the firms. The banks pay an exogenous gross interest rate $R^m > 1$ to the firms for their deposits. The bank only pays interest on the deposits that stay in the bank until the end of the term. To maximize the value of the banks, they choose loans to the firms $d'$ every period. These loans are subject to an intermediation cost. The banks charge a gross rate $R > 1$ for each unit of debt that the banks take as given.

The banks recursive problem is

$$V^{\mathrm{B}}(s, d, d^h, m, Z) = \max_{d'} \pi^{\mathrm{B}} + \mathbb{E}M(s'|s)V^{\mathrm{B}}(s', d', d'^h m', Z')$$

subject to

$$\pi^{\mathrm{B}} = R\, d - d' + m' - R^m m + \theta(R^m - 1)\sum_{n=\mathrm{z,u}} w_n l_n - Z\,\tau(d'),$$

where $\theta(R^m-1)\sum_{n=\mathrm{z,u}} w_n l_n$ corresponds to the early-withdrawn deposits of the firms that did not receive interest. $M(s'|s)$ is the household stochastic discount factor, and $s$ is the aggregate state. $Z > 0$ is the lending intermediation cost of new debt and is the source of uncertainty in the model. Notice that this cost plays the role of an intermediation premium. We define the exogenous changes to $Z$ as the credit-supply shock.[27] The intermediation cost follows an AR(1) process,

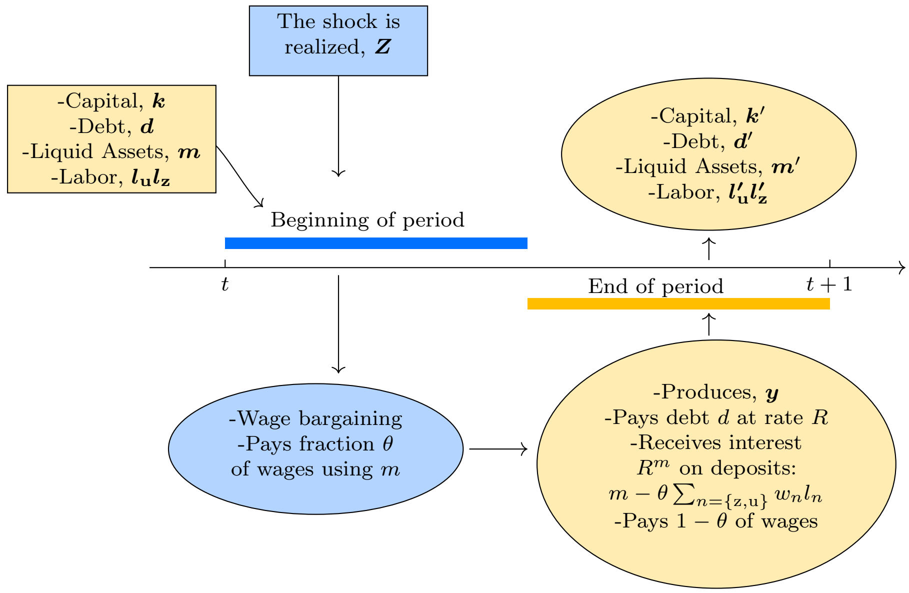
$$\log(Z_t) = \eta\log(Z_{t-1}) + \upsilon_t,$$

where $\upsilon \sim \mathcal{N}(0, \sigma_Z^2)$. We interpret a positive credit-supply shock as a reduction to the intermediation cost. A positive credit-supply shock increases borrowing supply, and, in equilibrium, reduces the cost of borrowing for the firm. The credit supply has an elasticity equal to $\tau(d')$, where $\tau'(d') > 0$ and $\tau''(d') < 0$. We include this feature to keep the model

[26] This form of preferences is commonly used in the literature of small open economies (Leyva and Urrutia, 2020; Alberola and Urrutia, 2020; Neumeyer and Perri, 2005).

[27] The role of the bank is as in Jeenas (2019).

**Figure 9:** Timing of the Firm's Decisions During the Period




tractable and simultaneously capture the risk of default in debt. The functional form for the elastic debt supply follows

$$\tau(b') = \frac{1}{2}\left(\frac{b'}{k}\right)^2.$$

## 5.3 Firms

The firms produce a final good using capital and two types of labor. Each firm enters the period with capital $k$, debt $d$, liquid assets $m$ in the form of deposits in the banks, and two types of labor: skilled $l_{\text{z}}$ and unskilled $l_{\text{u}}$. We divide the decisions within the period in two parts. Figure 9 illustrates the timing of the firm's decisions during the period.

In the morning of the period, after the credit-supply shock is realized, the firm bargains wages $w_{\text{z}}$ and $w_{\text{u}}$ with the workers in two separate markets, one for each type of labor. After this negotiation, the firms pay a fraction $\theta$ of the wage bill before production takes place. To pay it, the firms withdrawals $\theta \sum_{n=\{\text{z,u}\}} w_n l_n$ from its liquid assets deposited in the banks.

At the end of the period, production $y = f(k, l_{\text{u}}, l_{\text{z}})$ takes place. During the second part of the period, the firms pay their financial obligations with the banks $R\,d$, and collect interest on their deposits. Since the firms made early withdrawals from the banks, they only collect interest $R^m$ on the remaining deposits:

$$m - \theta \sum_{n=\{\text{z,u}\}} w_n l_n$$

Subsequently, to maximize the value of the firms, they choose the amount of capital $k'$, debt $d'$, liquid assets $m'$, and labor demand for the following period. When choosing debt, the firm takes the interest rate $R'$ as given, and cannot borrow at the deposit rate. This implies that there should be at least enough deposits to finance the working capital:

$$m \geq \theta \sum_{n=\{\mathrm{z},\mathrm{u}\}} w_n l_n.$$

When adjusting debt or capital, the firm pays a quadratic adjustment cost. The firm chooses labor demand by posting vacancies $v_n$ on each market $n$. Posting a vacancy on each market has an exogenous cost $\zeta_n$. Every period, an exogenous fraction of workers $\rho_n$ loses their jobs, while a fraction $q(\theta_n)$ of the firm vacancies are filled. Recall that $\theta_n$ is the market tightness. After reorganizing some terms, the recursive problem of the firm is

$$J(s,k,d,m,l_{\mathrm{u}},l_{\mathrm{z}},Z,) = \max_{l_n,k',b',m'} \pi^{\mathrm{F}} + \mathbb{E}\left(M(s'|s)J(s',k',d',m',l'_{\mathrm{u}},l'_{\mathrm{z}},Z')\right)$$

subject to

$$\begin{aligned}
\pi^{\mathrm{F}} &= f(k,l_{\mathrm{u}},l_{\mathrm{z}}) - \sum_{n=\{\mathrm{z},\mathrm{u}\}} w_n l_n - \theta(R^m-1)\sum_{n=\{\mathrm{z},\mathrm{u}\}} w_n l_n - \sum_{n=\{\mathrm{z},\mathrm{u}\}} \zeta_n v_n \\
&\quad - x - h(k',k) + d' - R\ d - \kappa(d',k) + R^m m - m' \\
x &= k' - (1-\delta)k \\
m &\geq \theta \sum_{n=\{\mathrm{z},\mathrm{u}\}} w_n l_n \\
l'_n &= (1-\rho_n)l_n + q(\theta_n)v_n,
\end{aligned}$$

where $x$ is investment, $h(k',k)$ are investment-adjustment costs, and $\kappa(d',k)$ are debt-adjustment costs.

To illustrate the mechanism of the substitution between low-skilled workers and capital and still keep the model simple and tractable, we use a functional form for the production function close to Vom Lehn (2020).[28]

$$f(k,l_{\mathrm{u}},l_{\mathrm{z}}) = \left(\mu(l_{\mathrm{z}})^{\eta_a} + (1-\mu)\left(\mu_r k^{\eta_r} + (1-\mu_r)(l_{\mathrm{u}})^{\eta_r}\right)^{\frac{\eta_a}{\eta_r}}\right)^{\frac{1}{\eta_a}}$$

The first term represents nonroutine activities that are only realized by skilled workers. The second term of the production function represents the routine activities. These activities can be realized either using capital or low-skilled labor. Given this production function, two

[28] Multiple functional forms studied in the literature can deliver capital–skill complementarities (Stokey, 1996; Krusell et al., 2000; Lafortune et al., 2019; Acemoglu and Autor, 2011; Vom Lehn, 2020).

parameters are key to understanding the effect of the credit-supply shock on wages. One is the substitution parameter between nonroutine and routine activities, $\eta_a$. The other is the substitution parameter between capital and low-skilled labor. $\eta_r$.

Similar to Neumeyer and Perri (2005), the portfolio-adjustment costs take the form

$$\kappa(d) = \frac{\kappa_t}{2} k \left( \frac{d'}{k} - \bar{d} \right)^2,$$

where $\bar{d}$ is the output debt ratio in steady state. The capital-adjustment costs take the form

$$h(k', k) = \frac{\phi}{2} k \left( \frac{k'}{k} - 1 \right)^2.$$

### 5.4 Search and wage bargaining

The number of employed workers is determined by the relationship between vacancies and unemployment—market tightness—$\theta_n = \frac{v_n}{u_n}$ in each of the markets. Unemployed workers get matched to current vacancies with a constant-returns-to-scale matching technology, $m(u_n, v_n)$:

$$p(\theta_n) u_n = q(\theta_n) v_n = m(u_n, v_n),$$

where $\phi_0 < 1$ and $\phi_1 < 1$. This matching technology says that the proportion of workers that switches from unemployment to employment must be equal to the fraction of vacancies that are filled every period.

To clear each labor market, the number of employed workers plus the number of unemployed workers must equal one.

$$1 = l_n + u_n$$

At the beginning of each period, firms and workers negotiate wages using a Nash bargaining solution following Shimer (2010). If the bargaining fails, the worker becomes unemployed. If it succeeds, she receives the negotiated wage $w_n$. The bargained wage is the solution to the following problem.

$$\arg\max_{w_n} \tilde{V}(w_n)^{\mu_{\mathrm{u}}} \tilde{J}(w_n(\lambda_{1f}))^{1-\mu_n},$$

where $\mu_{\mathrm{u}} \in [0, 1]$ is the workers' bargaining power. $\lambda_{1f}$ is the Lagrange multiplier of the liquid-assets constraint from the firms' optimization problem. It is important to notice that to guarantee a solution, the firm always must have enough deposits to pay wages. $\tilde{V}_n(w_n)$ is the marginal benefit to the household for having an extra worker employed at the current level of consumption, savings, and rate of unemployment. $\tilde{J}(w_n(\lambda_{1f}))$ is the value of the firm for hiring an extra worker at the current firm conditions. We derive $\tilde{V}_n(w_n)$ and $\tilde{J}(w_n(\lambda_{1f}))$

in Appendix D.1. Our solution is equivalent to the canonical search model in Shimer (2010).

### 5.5 Equilibrium and discussion of the mechanisms

The equilibrium is defined as follows. Given initial conditions $k_0$, $d_0$, and $m_0$, contingent state $s$ and a realization of the shock in $Z_t$, and a steady-state debt holdings position $\bar{d}$, an equilibrium is a sequence of allocations—$k_t$, $c_t$, $d_t$, $m_t$—and prices—$w_{\mathrm{z}t}$, $w_{\mathrm{u}t}$, $R$, $M(s'|s)$—such that all the markets clear. The household holds a trade deficit with the rest of the world.

To analyze the effect of a positive credit-supply shock on employment and wages, we analyze first the effect on the borrowing interest rate. From the banks' problem, credit supply is given by

$$\mathbb{E}M(s'|s)R' = (1 + Z\,\tau'(d'))$$

Recall that $\mathbb{E}M(s'|s) = \beta\mathbb{E}\frac{u_1(c',l'_{\mathrm{z}},l'_{\mathrm{u}})}{u_1(c,l_{\mathrm{z}},l_{\mathrm{u}})}$ is the stochastic discount factor from the household problem. We interpret $\frac{1}{M(s'|s)}$ as the return on savings for the household. This means that a reduction of the borrowing cost reduces the gap between the household savings rate and the firms' borrowing rate.

Credit demand is given by the firms' first-order condition for debt:

$$(1 - \kappa_1(d',k)) = \mathbb{E}\left(M(s'|s)R'\right).$$

Therefore, as a result of a positive credit-supply shock, the firms increase their debt level. The firms use this new debt to finance investment. They increase the amount of their capital stock following the firms' first-order condition for capital:

$$\left(1 + h_1(k',k)\right) = E\left(M(s'|s)\left(f_1(k',l'_{\mathrm{u}},l'_{\mathrm{z}}) + 1 - \delta + h_2(k'',k') + \kappa_2(d'',k')\right)\right).$$

The firm increases the capital stock to equalize the marginal product of capital, including the capital- and debt-adjustment costs, with the cost of borrowing.

Notice that the presence of the working-capital constraint to finance wages induces a gap between the household's return on savings and the firms' return to liquid assets, $R^m$. The firms' first-order condition for the liquid asset is given by

$$1 = \mathbb{E}M(s'|s)\left(R^m + \lambda'_{f1}\right),$$

where $\lambda_{f1}$ is the Lagrange multiplier for the money-holdings constraint. Because $R^m$ is fixed, when the constraint binds, a reduction in the intermediation cost increases the shadow cost of liquid asset holdings, $\lambda_{f1}$. This effect has an immediate implication for labor demand.

Because firms use liquid assets to finance working capital, increasing debt demand depresses labor demand. After the Nash bargaining process, labor demand comes from

$$w_{\mathrm{u}} = \left( \mu_{\mathrm{u}} MPL_{\mathrm{u}} + \mu_{\mathrm{u}} \zeta_{\mathrm{u}} \theta_{\mathrm{u}} + \frac{(1-\mu)\phi l_{\mathrm{u}}^{(\nu-1)}}{u_1(c, l_{\mathrm{z}}, l_{\mathrm{u}})} \right) \times \frac{1}{1 + \mu_{\mathrm{u}}(R^m - 1 + \lambda_{f1})\theta}$$

$$w_{\mathrm{z}} = \left( \mu_{\mathrm{z}} MPL_{\mathrm{z}} + \mu_{\mathrm{z}} \zeta_{\mathrm{z}} \theta_{\mathrm{z}} + \frac{(1-\mu)\phi l_{\mathrm{z}}^{(\nu-1)}}{u_1(c, l_{\mathrm{z}}, l_{\mathrm{u}})} \right) \times \frac{1}{1 + \mu_{\mathrm{z}}(R^m - 1 + \lambda_{f1})\theta},$$

where $MPL_{\mathrm{u}}$ and $MPL_{\mathrm{z}}$ are the marginal products of labor of unskilled and skilled workers, respectively. In Appendix D.1 we solve for the wage bargaining problem in detail.

The presence of these two mechanisms—capital–low-skill substitutability and a liquid asset to finance working capital—affect labor demand in two ways. First, when firms are unconstrained, that is $\theta = 0$, changes in wages and employment are solely determined by the production function. The overall effect of a positive credit-supply shock on average wages and employment will be determined by the elasticity of substitution between capital and unskilled workers in the following way. The marginal product of labor of both types of workers is increasing in the capital stock. The magnitude of the average effect depends in how the firm wants to substitute capital for low- or high-skill workers. A positive credit-supply shock increases labor demand for both types of workers. To connect this intuition with our empirical results, we imagine that a high-liquidity firm in the data corresponds to a firm with no working capital constraint, meaning no restrictions in the money holdings.

Second, when the firm is constrained, $\theta > 0$, a positive credit-supply shock reduces the firms' money holdings, and tightens the constraint, $\lambda_{f1}$. From the money-demand equation, we can observe that this reduces labor demand. It is important to notice that the effect is not necessarily symmetric for both types of workers. When the firm is constrained, two opposing forces determine labor demand for skilled workers—the capital–low-skill substitutability or the working-capital constraint. The total effect will depend on which effect dominates. In terms of average wages and employment, the effect is also ambiguous. Average wages can increase if labor demand for unskilled workers substantially decreases.

## 5.6 Quantitative analysis

### 5.6.1 Calibration

We calibrate the model to quantitatively assess the importance of the mechanisms in explaining the empirical results. To do so, we calibrate the model to match the main characteristics of our data. In this sense, we estimate an AR(1) process of the credit-supply shock at the bank level to obtain $\rho$ and $\sigma_Z$. We find that $\rho = 0.37$ and $\sigma_Z = 0.19$ (see Table 11 in the appendices). Note that the shock is not very persistent, and it is highly volatile.

Key in the model are the differences between the household discount factor, the deposits rate, and the borrowing rate. We calibrate these parameters using our credit data and aggregate data from Colombia as follows. We use the average annual deposits rate reported by the Colombian central bank for 2008–2018. Since the rates are in pesos, we use the CPI to calculate annual inflation and use only real values.

We calibrate the deposit rate using the average fixed-term deposits rate with annual maturity. Then, we set $R^m = 1.0261$. We equate the discount factor to the inverse of the interbanking rate, the rate for credit operations between banks. Since our model requires $1/\beta$ to be the median rate in the market, we use the fifth percentile of the interbanking rate during 2008–2018 and set $\beta = 0.9598$. Notice that this number is close to the calibration in Neumeyer and Perri (2005) for the Argentinian economy. Finally, we set the steady-state borrowing rate to match the average corporate-credit borrowing rate. Table 12 in the appendices reports summary statistics for these three rates.

We use data from the firms' financial reports and some aggregate data at the national level for the firms' parameters. The key targeted moments in our model are the steady-state debt-to-capital ratio, $\frac{d^*}{k^*}$, and the on-impact effect on investment and debt. To match these moments, we measure $\frac{d^*}{k^*}$ as the average leverage (See Table 1). We set $\kappa$ to match the effect on debt and investment. We calibrate $\bar{d}$ and $Z^*$ to satisfy the firms' and banks' steady-state Euler debt equations. Since the volatility of investment is determined in the model by the portfolio-adjustment costs and $\frac{d^*}{k^*}$, we set $\phi$ to a minimum. We calibrate the depreciation rate to match the average annual depreciation rate in our data. The depreciation rate implied by the data is higher than usual values. Thus, we compare our results using the average depreciation rate for Colombia using data from PWT 9.1. (See, Table 13). For the production function, we use the same parameters in Vom Lehn (2020). To evaluate the role of the working capital channel, we use $\theta = 1$, assuming that the firm must pay all of its wage bill before production takes place.

Because we do not observe hours or additional characteristics in the data, we follow the literature to set the household parameters. The key parameter in our model is the elasticity of labor supply. Neumeyer and Perri (2005) use an intermediate value between Mendoza (1991) and Correia et al. (1995). It is important to highlight that the implied value of the elasticity of labor supply of these papers (1.66) is large. Restrepo-Echavarria (2014) and Alberola and Urrutia (2020) use an inelastic labor supply to study the role of informality on developing economies and Mexico specifically. We use the estimates in Prada-Sarmiento and Rojas (2009) for the elasticity of labor supply for Colombia. This number is close to the value in Leyva and Urrutia (2020) for Mexico. This value is still low compared to Neumeyer and Perri (2005), without assuming an inelastic labor supply. It is consistent with the micro estimates of the Frisch elasticity of labor supply in Peterman (2016). We set the disutility

**Table 4:** Calibration of the Baseline Economy

| Parameter | Symbol | Value | Source |
|---|---|---|---|
| | | *Using micro data* | |
| Persistence shock | $\eta$ | 0.3698 | AR(1) OLS estimation |
| Std. dev shock | $\sigma_Z$ | 0.1911 | AR(1) OLS estimation |
| Steady-state debt holdings | $\bar{d}$ | 0.48 | To match avg. leverage |
| Portfolio-adjustment costs | $\kappa$ | 0.9 | Match estimated debt |
| Investment-adjustment costs | $\phi$ | 0.5 | Match estimated debt |
| | | *Colombian aggregate data* | |
| Discount factor | $\beta$ | 0.9241 | Inverse p5 interbank rate |
| Steady-state int. cost | $\tau$ | 0.1053 | Diff. corp. and borrowing rate |
| Steady-state unemployment rate | $\bar{u}_n$ | 0.102 | Unemployment rate |
| | | *Literature* | |
| Depreciation | $\delta$ | 0.0844 | Standard lit. |
| Capital weight | $\mu_r$ | 0.39 | Vom Lehn (2020) |
| Skilled weight | $\mu_a$ | 0.38 | Vom Lehn (2020) |
| Substitution capital–unskilled labor | $\eta_r$ | 0.4 | Vom Lehn (2020) |
| Substitution skilled–routine | $\eta_a$ | −2.22 | Vom Lehn (2020) |
| Risk aversion | $\sigma$ | 2 | Standard lit. |
| Elasticity of labor supply | $\frac{1}{\nu-1}$ | 0.32 | Leyva and Urrutia (2020) |
| Disutility of labor | $\psi$ | 1.8 | Neumeyer and Perri (2005) |
| Nash bargaining parameters | $\mu_{\mathrm{u}}$ | 0.5 | Standard lit. |
| Matching function | $\phi_0\phi_1$ | 0.5 | Standard lit. |
| Steady-state probability of filling a vacancy | $\bar{q}(\theta_n)$ | 0.7 | Standard lit. |

of labor supply parameter, $\psi$, to 1.8 following Neumeyer and Perri (2005).

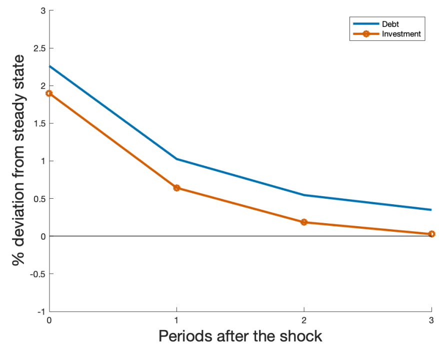
For the search-block parameters, we calibrate the cost of posting a vacancy, $\zeta_n$, and the probability of unemployment, $\rho_n$, in each market to match the average unemployment rate in Colombia during the sample period of 10.02% and the steady-state probability filling a vacancy of 0.7. We set the Nash bargaining parameters, $\mu_{\mathrm{u}}$, and the matching function parameters, $\phi_0$ and $\phi_1$, all to 0.5. Table 4 summarizes our calibration.

### 5.6.2 Simulations

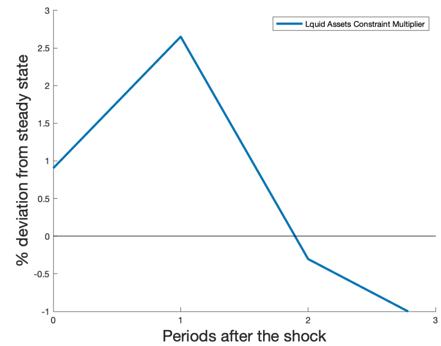
To compare the model with the data, we focus on the impulse response functions of debt, gross investment, employment, average wages, and wages by type of worker. Recall, to keep the model simple, we understand unskilled wages as equivalent to wages below the median income in the data, and skilled wages as wages above the median. We start by simulating the baseline model. For these results we assume that the constraints always bind. Figure 10a shows the effect on debt and gross investment. The horizontal axis in this figure shows the periods after the shock. The vertical axis shows the percentage response to a one-standard-deviation shock. Recall that we calibrate the shock to have the same persistence as the estimated shock in the data. As we discussed before, we target the response of debt to

**Figure 10:** Impulse Response Functions to a Positive Credit-Supply Shock of Investment, Debt, Wages, and Employment

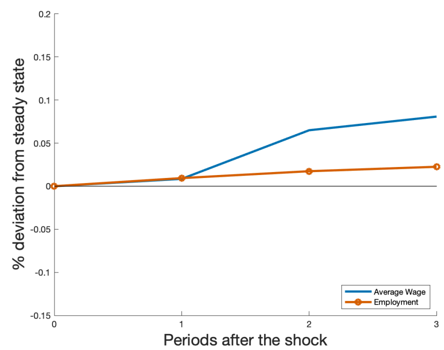
**(a)** Debt and Gross Investment



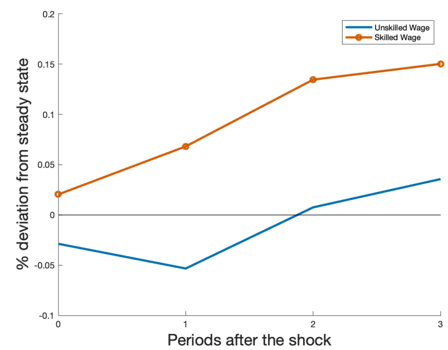

**(b)** Shadow Value of Liquid Assets




**(c)** Employment and Average Wages




**(d)** Low and High Wages



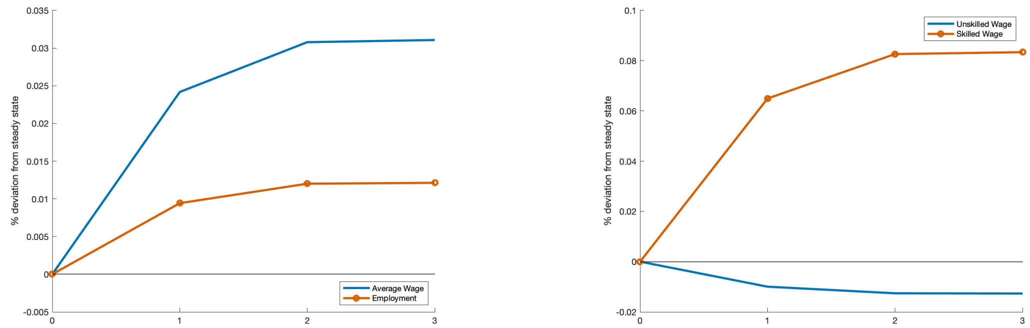

**Note:** Impulse response functions for the baseline model simulations.

match the estimates' response in the data. All the remaining effects in the model are results. As we expected, in response to a positive credit-supply shock, the capital stock increases by 2%, which is very close to the change of 1.8% in the data. Figure 10b shows the effect on the shadow value of holding money. With this figure, we want to highlight the trade-off firms face. A positive credit-supply shock increases the opportunity cost of holding liquid assets and the benefit of investment. Figure 19 in the appendices shows the effects on the borrowing interest rate and money holdings.

Figures 10c and 10d show the labor market results. Figure 10c shows the effect on employment and average wages. The model predicts a small positive effect on both average wages and employment. These two results are consistent with our empirical findings. The model, however, predicts a larger effect on average wages two and three periods after the shock. The reason for this discrepancy is that, compared to the data, demand for high-skill workers is more responsive to a positive credit-supply shock. Figure 10d shows the effect on wages by type of worker, demonstrating how both mechanisms interact. On impact, similarly to Figure 3 in the empirics, wages of low-skilled workers decline, while those of the high-

**Figure 11:** Impulse Response Functions to a Positive Credit-Supply Shock to Wages and Employment for Firms With no Working Capital

**(a)** Employment and Average Wage **(b)** Wages




**Note:** Impulse response functions for the model without working capital.

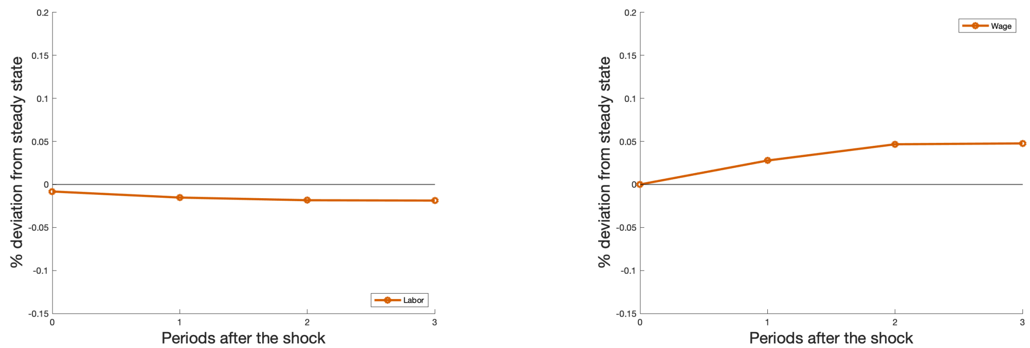
skilled workers increase. The negative effect lasts for two periods for low-income workers, while it becomes positive for high-income workers. In other words, one period after the shock, working capital dominates the production function. As the liquid-assets constraint becomes binds less, the effect of capital–skill substitutability takes relevance. The key parameter to determine which effect dominates one period after the shock is the elasticity of substitution between capital and low-income workers. As low-income workers substitute for capital more exactly, the negative effect on low-income workers disappears. Figure 20 in the appendices shows the sensitivity analysis for capital–low-skilled substitutability. This parameter is of particular relevance for the effect three years after the shock.

To understand the effect of a positive credit-supply shock on unconstrained firms, we simulate the model with no working capital (Figure 11). One point to emphasize is the magnitude of the change in debt and investment compared with the baseline model (see Figure 21 in the appendices). As with the data, our unconstrained firm is as responsive as the constrained firm in terms of debt and investment. Figure 11a shows the effects on average wages and employment. Contrary to what we observe with the baseline model, average wages decrease and employment increases for two reasons. First, Figure 11b shows the effect on low-skilled and high-skilled wages. Similarly to the data, the negative effect on low-income workers is half of the constrained firm's effect. Moreover, the effect on high-skilled wages is also larger. As a result, both employment and average wages increase more compared to the constrained firm's results. In other words, because the firm faces a trade-off between increasing capital and using liquid funds to pay for the working capital, we only observe the effect of the capital–low-skilled substitutability channel.

Finally, we explore the effects of a positive credit-supply shock on a firm with just one type of labor and a working-capital constraint (Figure 12). From this experiment, it is im-

**Figure 12:** Impulse Response Functions to a Positive Credit-Supply Shock for Wages and Employment in Firms With Only One Type of Labor

**(a)** Wage **(b)** Employment




**Note:** Impulse response functions for the model with just one type of labor.

portant to emphasize that the effect on wages and employment is always negative, regardless of the elasticity of labor supply. Moving from the two extremes of the baseline model, no working capital and one type of labor makes us depart further from the empirical results. This suggests that the small changes in average wages and employment could potentially be explained by the interaction of the two mechanisms. These two forces eliminate the effect on labor demand for high-income workers, so we only observe changes at the bottom half of the distribution in the data.

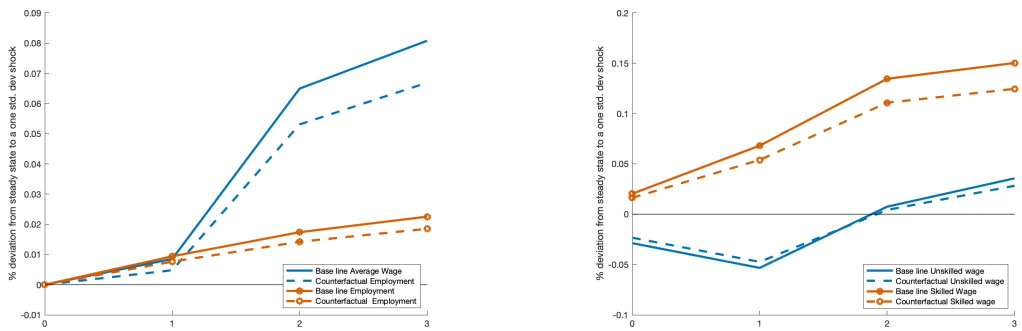
#### 5.6.3 Counterfactual

From our empirical results and the model, we show that changes to credit supply represent a limited channel to produce changes in average wages and employment. More importantly, changes to credit supply have an effect on wage inequality. Also from our model, any policy that aims to expand corporate credit to affect wages must be accompanied by additional mechanisms to make liquidity constraints bind less. In this section, we study how permanent changes in the intermediation premium, $\bar{\tau}$, change the response of employment and wages to a credit-supply shock. Studying changes in the intermediation premium is of particular interest in terms of policy because it is equivalent to asking, "What would happen if we make banks more efficient?"

Our experiment consists of reducing $\bar{\tau}$ by 20%. A reduction of 20% in $\bar{\tau}$ is equivalent to reducing the steady-state borrowing rate from 8% to 7%. Figure 13 compares the impulse response functions of the baseline model with that of the counterfactual. Panel 13a compares the effect on average wages and employment, Panel 13b shows the effect on skilled and unskilled wages. The result shows that when the intermediation premium is permanently smaller, low-skilled wages do not decrease as much as they do in the baseline model. For

**Figure 13:** Comparing the Impulse Response Functions of a Positive Credit-Supply Shock on Employment and Wages for Different Levels of a 20% Lower Intermediation Premium

**(a)** Employment and Average Wage **(b)** Wages




**Note:** Impulse response functions to the model without working capital.

instance, one year after the shock, low-skilled wages are 5.93% higher compared to the baseline model. High-skilled wages, on the other hand do not increase as much as in the baseline model. One year after the shock, high-skilled wages are 8.3% lower compared to the baseline model. As a result, the response to a credit-supply shock of average wages and employment is even smaller when the intermediation premium is permanently lower.

This means that reducing the intermediation premium helps reduce the wage gap between skilled and unskilled workers. However, two and three years after the shock, the firm does not increase high-skilled wages as much compared to the baseline model. This translates to lower average wages and also lower employment.

The mechanism works as follows. By improving the bank's ability to turn deposits into firm debt, the debt supply becomes less responsive to an equivalent shock (see Figure 22a in the appendices). Thus, in response to a positive credit-supply shock, debt increases four percentage points less than in the baseline model. This translates to a smaller increase in the capital stock: The investment opportunity is not as great (see Figure 22b in the appendices). From the capital—skill-substitutability channel, the firm does not decrease demand for unskilled workers compared to the baseline model. At the same time, the trade-off between investment and holding liquid assets goes down one period after the shock (see Figures 22c and 22d in the appendices). As a result, we observe that employment and average wages do not decrease as much compared to the baseline model. However, since the firm did not increase its capital stock, the long-term effect hurts high-skilled workers, employment, and average wages. In this sense, when we reduce the intermediation cost by making banks more efficient, the liquidity constraint becomes less relevant in the long run.

## 6 Conclusions

In this paper, we ask how access to the corporate credit supply affects employment and wages outside financial-crisis episodes. To answer this question, we create a unique data set from Colombia linking banks, firms, and workers and identify idiosyncratic credit-supply shocks from 2008–2018. Using these credit-supply shocks, we document three facts. First, we confirm previous results from the literature (Khwaja and Mian, 2008) and find evidence that more corporate credit availability increases borrowing and investment. We find that employment and average wages do not change in response to idiosyncratic credit-supply shocks. Second, we exploit the richness of our data set to estimate the effect of the credit-supply shock at the worker level. We find that wages at the bottom half of the distribution go down during the first two years after the credit-supply shock. Third, we find evidence that the response is uneven across firms. Firms with high liquid-asset holdings increase in scale in response to a corporate credit-supply shock. In contrast, firms with low liquid-asset holdings face a trade-off between increasing capital and increasing labor demand for all types of workers. As a result, these low-liquidity firms reduce demand for low-income workers and increase it for high-income workers. The positive effect on employment and average wages cancels out for these firms.

To explain how the liquidity channel interacts with the capital–labor substitutability channel, we develop a parsimonious small-open-economy model with working capital. We extend the seminal work by Neumeyer and Perri (2005) and add liquid assets to finance working capital, two types of labor, and "passthrough" banks (Jeenas, 2019), and a search block. We simulate our baseline model and find that the presence of both mechanisms can rationalize our empirical findings. Our model replicates the finding on debt and gross investment. When firms face liquidity constraints to finance labor with different types of labor, the effect on low-income wages is always negative. However, the effect on high-income workers depends on which effect dominates, the positive effect of the capital–skill mechanism or the negative effect of the working capital. As a result, the effect of a positive credit-supply shock on employment and average wages is small. The sign depends on the elasticity of labor supply and on the elasticity of substitution between capital and low-skill workers.

To verify our results, we simulate our model in two extreme cases. First, we turn off the working-capital mechanism. The result for debt and gross investment remains positive. In the labor market, demand increases (decreases ) for high-income (low-income) workers. Thus, employment increases and the effect on average wages depends again on the elasticity of substitution between capital and low-skill workers. Second, we turn off the capital–skill mechanism, and simulate the model with only one type of worker. In this case, employment and wages go down permanently in response to the credit-supply shock.

Finally, we run a counterfactual in which the intermediation premium is permanently lower. This means that we permanently reduce the difference between the deposit and borrowing rate. This experiment is equivalent to making banks more efficient in their passthrough function. With this experiment, we conclude that if a policymaker wants to make banks more efficient, there are two implications for responses to a credit-supply shock. The response of credit supply is smaller, thus the effect on the capital stock is not as pronounced. For the firms, this has two implications. First, it reduces the trade-off between financing labor and increasing investment. Second, it has distributional implications. The firm is willing to hire more unskilled workers at the expense of not expanding in scale.

The findings in this paper are of particular interest for policymakers for two reasons. First, by linking banks, firms, and workers, we can assess whether expansions of corporate credit are likely to increase wages, or reduce labor income inequality, in developing countries. Our results suggest that expanding credit produces few changes in average wages and employment, but it can potentially increase labor-income inequality. Second, our model indicates that any policy with the objective of increasing corporate credit and wages needs to be accompanied by additional mechanisms to reduce liquidity constraints.

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# A Appendix: Data

## A.1 Credit

Banks in Colombia make quarterly reports about all of their open credit operations to the *Superintendencia Financiera*, the government agency in charge of overseeing the financial markets. This report is called *Formato 341* and contains detailed information about capital, and interest payments, interest rates, default, and maturity. Each bank makes separate reports for commercial credit, mortgages, consumption loans, and microcredit. We use data only for commercial credit issued between January 2004 and December 2018 to firms that use a firm identifier, *NIT*. We organize the data in three steps. First, we clean the original reports to remove outliers and transactions with incomplete information. Then we aggregate these data at the firm and bank levels and use information on the last quarter of the year to estimate the annual credit shock using all transactions from each firm–bank pair.

To remove outliers, we first keep credits with maturity greater than 1 day and less than 90 years. We drop all transactions missing the lending institution. After this, we recover each credit operation history, and we keep loans for which we have the entire history so we can verify the maturity. To do so, we first define a transaction identifier: Bank–Initial Date–Final Date–Firm id. We say that a loan is complete if the first observation corresponds to the initial date, and the last observation corresponds to final credit date. With the incomplete loans, we consider that there might be a problem in some reports, so we use a fuzzy-merge algorithm to recover the missing dates. If after the fuzzy merge, we have the entire history, we keep the transaction; if not, we drop it. If, after identifying the credit history, there are two operations with identical credit identifier but different capital stocks and interest rates, we consider them as unique loans and average the interest rate by date and sum the capital owed. After this, we drop observations with National Identifications and credit issued using firm IDs with length less than eight (a data-entry error). We drop credits if the interest rate is higher than the maximum legal interest rate of the period (33.51% for 2017-1), and loans where the number of default days is greater than the maturity. We drop credits below 10,000 COP (around 3 USD). We use the initial interest rate for each credit as the interest rate. If the reported interest rate is less than 1%, we multiply it by 100 on the assumption that it is a data-entry error. The reason is that these credits are on average of 200,000 USD and the inflation rate in Colombia is on average greater than 3%. We define debt as the sum of capital, interest and other obligations for each transaction.

We use this data as input to estimate the credit shock and to compute bank- and firm-level financial data.[29]

After removing outliers and data-entry errors as we describe above, we aggregate the data at the firm and bank levels separately. At this point, we do not consider the history of each credit. Instead, we use information on the opening date of each transaction. We define the average credit amount on date $t$, the average interest rate, the probability of default as a dummy if the firm ever defaulted on a credit. We define the number of credits as the number of open credits at date $t$ with all banks, and total new debt as the total amount of new debt with all banks at date $t$. To calculate the number of relationships per firm, we go back to the original data and keep the initial and the final date per operation and the bank. We reshape the data and count the number of open credit operations. We count as an open relationship the oldest initial date with a bank, and close the relationship if on the final date of the operation there are no more open credits with that bank.

## A.2 Banks

In the credit data, each financial institution has a banking identifier, which differs from the NIT, and the names are not reported. We use information on the banks' balance sheets to recover the bank name. In this sense, our sample is restricted to credit issued from financial institutions registered as banks.

We use information on the banks' financial reports to define our banking sample. We keep banks with more than eight years in the market and banks that entered the market after 2008. This leaves us with a sample of 29 possible banks. We use each December financial report to compute the banks' size and stock of commercial debt to validate our credit-supply shock, as well as the additional measures of bank health. We define a dividends dummy if the bank reports having dividends to pay in liabilities. We compute the CASA ratio as the ratio of checking and savings account deposits to total deposits, and capital as the book value of the net worth to total liabilities.

To compute the banking health measures from the balance sheet, we develop a matching methodology between financial reports. First, we keep for each month and year the groups and classes, the broader classification in the financial report, and store the names of the accounts for each year. Then we merge by year the accounts classification by class and group. The goal in this step is to compare if the numeric classification corresponds to the variable description. In this sense, we compare the difference in the text description of each account with the previous year, and define a ratio as the number of variables with a different variable description between year $t$ and year $t-1$. We identify a different accounting methodology if the difference in description between two years is greater than 12%. We find that the

[29] Credit_Full_Comm_Quart.dta.

**Table 5:** Summary Statistics: Banks

| | Mean | Std. Dev | P95 | P5 | $N$ |
|---|---|---|---|---|---|
| $\Delta$ log Commercial credit | 0.07 | 0.17 | 0.29 | $-0.12$ | 143 |
| Equity to assets | 8.86 | 2.53 | 13.85 | 5.28 | 144 |
| Dividends dummy | 0.79 | 0.41 | 1.00 | 0.00 | 144 |
| CASA | 0.59 | 0.14 | 0.81 | 0.34 | 144 |
| Capital adequacy | 0.01 | 0.02 | 0.08 | 0.00 | 144 |

**Note:** Data Source: 31 December bank financial reports from Superintendencia Financiera de Colombia.

**Table 6:** Summary Statistics: Banking Shock

| | Mean | Std. Dev | P95 | P5 | $N$ |
|---|---|---|---|---|---|
| Banking shock$_{ft}$ | 0.05 | 0.13 | 0.27 | $-0.12$ | 57,168 |

**Note:** Summary Statistics of the credit-supply shock

variable descriptions changed in 2015. Between 2014 and 2015, 81% of the descriptions are different. After identifying the differences, we manually looked for the variables of interest in each accounting methodology.

### A.3 Credit shock

To estimate the credit shock, we follow Amiti and Weinstein (2018). First, we keep credit operations with banks in our final banking sample. Then, to estimate the annual credit-supply shock, we keep the debt stock per transaction on the fourth quarter of the year. The reason to do this is that the firm's financial reports are at the end of the year. Then, we generate the total debt stock per firm and bank. We drop banks with fewer than five relationships. Only one bank in our sample had this issue, BWWB, a small bank that entered the market in 2012. Then we estimate the credit-supply shocks per year (Amiti and Weinstein, 2018). After this, we compute the credit-supply shock as a weighted average of the banking portfolio per firm.

### A.4 *Super-Sociedades*

We use data from 2001–2015 from *Super-Sociedades.* Each firm reports every year its balance sheet and income statement with their corresponding appendices. We identify two different accounting methodologies in this period: 2001–2010 Colombian old PUC accounts and 2007–2015 Colombia Updated PUC accounts. We consider that the accounting methodology is different if less than 90% of the form identifiers are identical between two consecutive years.

To define an accounting methodology, and to map variables between the 2000 methodology and the 2007 methodology, we proceed in two steps. First, we list all the possible names, second we merge identical names using a fuzzy-merge algorithm. The following two subsections explain in detail how we proceed.

### A.4.1 Variable names

All firms submit an annual report in a format classifies information in four ways. The broader category is called *formato*, where they select the type of report. For example, the balance sheet corresponds to one of these broad categories, as do the income statement and the general appendices in a regular financial report. Inside each of these forms, firms are asked to enter particular information. Each observation is going to correspond to a numbered category, row, and column—*Unidad de captura, fila, and Columna* correspondingly in Spanish. We get the reports as plain files where we do not have the variable name, just the locator. To identify the variable names and compare them between years, we create a unique identifier as $f\_ca\_r\_co$, where we recover the corresponding form, category, row and column were it was recorded. Then we use a list of variable names provided by *Super-Sociedades*, one for 2000, one for 2007. This list has more possible variables than the number of variables in the original data, so we merge the unique codes, $f\_ca\_r\_co$, from the list of variable names with each unique code per year in the data. Years 2001 to 2006 are merged with the list of variables names in 2000 and years 2007 to 2015 are merged with the variable names in 2007. We keep a variable if we observe the name in the list of names, and if it is available in at least one year per methodology. After we identify the names of the variables, we find 33 general forms in 2007's and 40 forms in 2000's methodology.

### A.4.2 Form matching

To compare information between methodologies, we first match the general forms (*Formatos*) using a fuzzy-merge algorithm. For each available form in 2007's methodology, we compare merge names with 2000's algorithm and consider a match by the minimum difference between the texts. Using this algorithm, we merge 29 formatos and verify manually that the remaining four do not have a correspondence in 2000's methodology. Table 7 shows the correspondence between forms. The first two columns show the original names in Spanish for 2007 and 2000, while the last two show the corresponding numbers.

After identifying the correspondence between the aggregated forms, we compare the remaining parts of the unique identifiers: row, category and columns. This step is mostly manual. We compare form by form due to substantial changes in the structure. For each form, we compare the number of rows, columns, and categories, and merge one by one. In this step, we assign labels and variables in English. The final result is a list of all variables available, with the corresponding code in 2007's methodology, the 2007 code, and all names.

**Table 7:** Matching General Forms (*Formatos*)

| Form Name 07 | Form Name 2000 | Form Number 07 | Form Number 00 |
|---|---|---|---|
| caratula | | 1 | . |
| Anexo_1: ingresos de operación | Anexo 01 ingresos de operación | 100 | 4000 |
| Anexo_2: costo de ventas y de prestación de servicios | Anexo 02 costo de ventas y de prestación de servicios | 200 | 5000 |
| Anexo_3: costos indirectos y gastos operacionales de administración y de ventas | Anexo 03 costos indirecta y gastos operacionales de admón y ventas | 300 | 6000 |
| Anexo_4: costos y gastos de personal | Anexo 04 costos y gastos de personal | 400 | 7000 |
| Anexo_5: ingresos y gastos no operacionales | Anexo 05 ingresos y gastos no operacionales | 500 | 8100 |
| Anexo_6: ingresos y gastos financieros | Anexo 06 ingresos y gastos financieros | 600 | 9100 |
| Anexo_7: inversiones en sociedades | Anexo 07a inversiones en sociedades | 700 | 10100 |
| Anexo_7a1: inversiones en renta fija | Anexo 07b inversiones renta fija | 701 | 10200 |
| Anexo_7a2: método de participación patrimonial | Anexo 07c método de participación patrimonial | 702 | 10300 |
| Anexo_8a: deudores corto plazo | | 801 | . |
| Anexo_8b: deudores largo plazo | | 802 | . |
| Anexo_9: propiedades planta y equipo | Anexo 09 propiedades planta y equipo | 900 | 12000 |
| Anexo_10: obligaciones financieras y proveedores | Anexo 10a obligaciones financieras y proveedores | 1000 | 13100 |
| Anexo_10a: obligaciones financieras y proveedores—submenú | Anexo 10a obligaciones financieras y proveedores | 1001 | 13100 |
| Anexo_11: movimiento de reservas y revalorización del patrimonio | Anexo 11 movimiento de reservas y de la revalorización del patrimonio | 1100 | 14000 |
| Anexo_12: accionistas o socios | Anexo 12a accionistas o socios | 1200 | 15100 |
| Anexo_12a: clase de inversionistas de acciones en circ, cuotas o partes de int. social poseídas | Anexo 12b clases de inversionistas de acciones en circulación | 1201 | 15200 |
| Anexo_12b: valor intrínseco | Anexo 12c valor intrínseco | 1202 | 15300 |
| Anexo_14: pensiones de jubilación | Anexo 14 pensiones de jubilación | 1400 | 17000 |
| Anexo_15: información general | Anexo 15a información general | 1500 | 18100 |
| Anexo_15a: derechos en fideicomiso | Anexo 15c derechos en fideicomisos | 1502 | 18300 |
| Anexo_15b: derechos en bienes recibidos en arrendamiento financiero (leasing) | Anexo 15d derechos en bienes recibidos en arriendo financiero (leasing) | 1503 | 18400 |
| Anexo_15c: movimientos en el exterior aumento del capital social | Anexo 15e movimiento en el exterior—aumento de capital social | 1504 | 18500 |
| Anexo_17: actividad de vivienda e inventarios | Anexo 17 actividad de vivienda—inventarios | 1700 | 20000 |
| Anexo_19: inventario de semovientes en administración directa | Anexo 19 inventario de semovientes en administración directa | 1900 | 22000 |
| Anexo_20: inventario de semovientes en deposito | Anexo 20a inventario de semovientes en deposito | 2000 | 23100 |
| Anexo_20a: inventario de semoviente en deposito | Anexo 20a inventario de semovientes en deposito | 2001 | 23100 |
| Anexo_20b: inventario de semovientes en deposito | Anexo 20a inventario de semovientes en deposito | 2002 | 23100 |
| Anexo_22: obligaciones con incumplimiento en los pagos | obligaciones con incumplimiento en los pagos | 2200 | 30 |
| Anexo_23: demandas ejecutivas para el pago de obligaciones mercantiles | | 2300 | . |
| estado de resultados | estado de resultados (g & p) | 2400 | 1000 |
| balance general | balance general | 2500 | 0 |

We use this methodology to match all the forms but the balance sheet. Given that the balance sheet accounts are divided between classes, groups, accounts, and subaccounts, and these are simultaneously divided in current and long-term accounts. We create a matching algorithm merging the codes. With these two procedures, we end up with 1,925 variables.

### A.4.3 Variables of interest

This section describes the variables we keep in the final database, their general forms of origin, and how we modify them. We divide our variables of interest into four categories: general information, balance sheet, liquidity constraints, international exposure, and labor. After categorizing the information, we first keep firms that have positive values for all assets and for which the basic accounting equation holds. We do this to ensure we have no substantial data-entry errors. Second, we verify that the report on capital—fixed assets—is always positive and that it contain no outliers. Then, if capital is missing in a particular year, but the column that reports capital from the previous year is not, we replace capital in the current year as the reported capital from the previous year. At this point, we ensure that we have no negative capital values on capital. If we do, we replace the missing observation; if the previous and following years are not missing, we impute the value as the average. Third, we drop firms if sales and operational costs are negative or that report a number of workers larger than 10% of the 2010 Colombian working-age population[30] or if the total wage bill is negative. Fourth, we use sectors and cities from the public report because firms' original reports contain more data-entry errors in the sector classification and cities, whereas the public reports have been corrected. We merge the city, region, and sector by NIT and year. From the sector and location, we leave the sector and city of the first observation if it is time variant. Finally, we drop firms if total assets, liabilities, equity or sales are missing or if the age of the firm is negative. We keep firms for which we have at least four years of data with no more than a single one-year gap. We impute the values for any gaps as the average between the previous and following years. After the imputation, we drop the firms at the top and bottom 1% of assets.

It is relevant to mention that all the variables in levels are in real thousands of 2018 USD. To do this we deflate each variable using the average monthly Colombian CPI the with base December 2018 and the COP/USD exchange rate from December 2018.

## A.5 Matching firms in PILA and Super-Sociedades

PILA uses worker and firm identifiers—*personabasicaid* and *id*, respectively—exclusive for this database. For 2010, the database provides a matching between the workers' identifiers,

[30] 38,693,000 from DANE.

a unique pair *cédulas–personabasicaid*, but does not provide the same for firms. Therefore, our task is to match the firms' identifiers, *NIT–id*.

To do so, we use *cédulas* of the legal representatives and accountants of the firms in Super-Sociedades during the period 2010–2015, and the matching of workers in PILA for 2010. Despite having information about the legal representatives and accountants, the link between firms is not straightforward for two reasons. First, it is possible that a person available in Super-Sociedades can have more than one job. This means that one *cédula* may be associated with more the one *NIT* and more than one *id*. Second, being a legal representative or an accountant to a firm does not necessarily imply that they are registered as workers of that firm. For example, an accountant can work for a firm $X$ providing accounting services, and can be registered as the accountant of firm $Y$, a client of firm's $X$. If this happens, this worker would be the accountant of firm $Y$ in Super-Sociedades and a worker of firm $X$ in PILA.

Therefore, our strategy is as follows. We assume that the first three legal representatives and main accountant of the firm in Super-Sociedades are actually workers of the firm. We consider that this is a reasonable assumption because our sample in Super-Sociedades is restricted to large firms in Colombia. Therefore, it is likely that they have a complex and well-organized corporate governance structure. That is, we assume that the CEO and main directors act as legal representatives, and that these firms are large enough to have at least their main accountant on their payroll. Using this assumption, we first restrict our sample to *cédulas* in PILA where the match between *personabasicaid* and *cédula* is correct, to pairs where *personabasicaid* and *cédula* are actually unique. Second, we create a *NIT–cédulas–personabasicaid* link per year in Super-Sociedades. Given that we assume that the legal representatives and accountants work for a large corporation, and that they hold important positions, we restrict our sample to wages above minimum wage not reported as independent workers. This step gives us a set of possible matches: For every firm in Super-Sociedades, we create a set of possible firms in PILA. Third, we follow an iterative process to eliminate possible *NIT–id* pairs from the information set based on stronger criteria. The next three sections describe in detail each of the previous steps.

### Step 1: Cleaning data-entry errors

Using the original match between *personabasicaid* and *cédulas*,[31] we remove data-entry errors, nonnumeric characters, and *cédulas* with fewer than eight digits.[32] We store this data as "cedulas_unicas.dta." Following a similar procedure, we use the original workers'

[31] file name: personabasicaid_allGta.

[32] Before 2004, the identification numbers had eight digits; starting in 2004 the sequence changed to ten digits. See registraduria.gov.co.

information in Super-Sociedades.[33] and create *NIT–cédula* pairs. Again, we remove data-entry errors, nonnumeric characters, and *cédulas* with fewer than eight digits. In contrast, we assume the NITs are free of the same data-entry errors (see Data Appendix A.4). Here, we restrict our sample to the first three legal representatives and the main accountant. We drop information about board members, the auditor, and other legal representatives and accountants. We store this data as "cedulas_SS_all-cedulas_unicas."

#### Step 2: Linking *NIT* to *cédula* to *personabasicaid*

In this step, we create two files. On the one hand, we have one *NIT–cédula–personabasicaid* triplet per year. Keeping the time dimension in this step is crucial, as well as the region–city code. We are going to use these two variables in the following steps. We name this file "cedulas_con_personasbasicaid_unicas." From this step, we have a universe of 35,364 firms. Out of those, 23,760 have more than two years of data, and 19,691 four or more. For the purpose of our estimations, we consider our universe to be the sample with four or more years of data.

On the other hand, we create an equivalent file using PILA, here we generate a *id–cédula*–personabasicaid triplet. To generate this triplet, we merge "cedulas_unicas.dta" with each December in PILA between 2010 and 2015. We only use December because Super-Sociedades has information about the annual financial reports, and these reports are presented on December 31 each year. We also restrict our sample to nonindependent workers with wages above minimum wage and below 0.01% of the distribution,[34] more than 15 days worked per month, and not double reported in the same firm. As before, we also store year and region–city code. We save this data as "cedulas_merge_pila'

#### Step 3: *NIT–id*

We use an iterative elimination process using a sequence of criteria. Regardless of the criterion used in each step, the process works as follows. First, we apply the criterion to both "cedulas_con_personasbasicaid_unicas" and "cedulas_merge_pila." We merge the databases using a one-to-one condition, keeping only those pairs that matched. Then, we verify that both *NIT* and *id* are unique, and drop the pair otherwise. We store the matches and update our information set. That is, we remove the identified *NITs* and *ids* from "cedulas_con_personasbasicaid_unicas" and "cedulas_merge_pila," respectively, and move to the following criterion. From this process, we identify 24,694 *NIT–id* pairs, 69.8% of the total firms. Of those, we recover 17,929 firms with more than two years of data, and 15,202 firms

[33] SuperSociedades_Formato1.dta.

[34] We make this last restriction because we consider that wages above this level could be data-entry errors.

with four or more years of data. These correspond to 75.5%, and 77.2% of the total number of firms with more than 2 and more than 4 years of data.

We start this process with the strongest criterion and work to the weakest:

1. **Unique–Unique**: We keep workers that only worked in one firm during the entire period (2010–2015) in both *Super-Sociedades* and *PILA*. We merge by *cédula*. Using this criterion, we obtain 14,330 firms.

2. **Unique in year–Unique in year**: We keep workers that worked in one firm per year in *Super-Sociedades* and that only worked in one firm per year in *PILA*. We merge by *cédula* and year. Using this criterion, we obtain 2,384 firms.

3. **Unique group by year–Unique group by year**: An individual could have had more than one job in either database per year, but the group of people working together may be unique in both *Super-Sociedades* and *PILA*. We create a new identifier, new_id, that sorts *cédulas* of each group, and merge by new_id and year. Using this criterion, we obtain 2,038 firms.

4. **Max mode by year–Max mode by year**: An individual could have had more than one job in either database per year, but there may be one firm in which the worker worked more years (the mode). The number of years must coincide in both databases. We use this criterion iteratively. We ranked the number of years worked per firm, we first use max mode, second mode, etc. We merge by *cédula* and mode. Using this criterion, we obtain 1,842 firms.

5. **Unique *cédula*, city, year–Unique *cédula*, city, year**: An individual could have had more than one job in either database per year, but the triplet *cédula*–year–city may be unique in *Super-Sociedades* and *PILA*. We merge by the triplet. Using this criterion, we obtain 1,564 firms.

6. **Unique group of workers, city, year–Unique group of workers, city, year**: An individual could have had more than one job, and the group of workers could have been together in more than one firm per year. However, the triplet group of workers–year–city may be unique in *Super-Sociedades* and in *PILA*. We merge by the triplet group of workers–year–city. Using this criterion, we obtain five firms.

7. **Unique *cédula*, region, year–Unique *cédula*, region, year**: Same as Criterion 5, but using region as the second element of the triplet. Using this criterion, we obtain 107 firms.

8. **Unique group of workers, region, year–Unique group of workers, region, year**: Same as Criterion 6, but using the worker's group as the first element of the triplet. Using this criterion, we obtain two firms.

9. **Repeat 1–4**: After the first elimination process, we repeat Steps 1–4 iteratively until we have no more matches. Let us use an example to explain why we repeat these steps. Suppose that we have one *cédula* associated with two *NITs* in *Super-Sociedades*, and that same *cédula* associated with two *ids* in *PILA*. We eliminate one *NIT* with Criterion 2, and one *id* with Criterion 3. If we then repeat Criterion 1, we can merge the remaining pair. Using this criterion, we obtain 1,104 firms.

10. **Unique–Unique but if *id* not unique after merge, use city**: One person only worked in one firm during the entire period (2010–2015) in *Super-Sociedades* and in *PILA*. We merge by *cédula* and conclude that a *NIT* corresponds to an *id*. Here, we only drop if *NIT* is not unique, but we do not drop if *id* is not unique. Rather, we compare cities from both sources and keep those with the same reported city. Then we drop if *id* is not unique. Using this criterion, we obtain 98 firms.

11. **Unique–Unique but if *id* not unique after merge, use region**: Same as Criterion 10, but using region as the second condition. Using this criterion, we obtain 449 firms.

12. **Repeat 1**: Using the same argument as in Criterion 9, we repeat Criterion 1 iteratively. At this point, we have too little information to repeat Criteria 2–4. Using this criterion, we obtain 405 firms.

13. **Unique group–Unique group but if *id* not unique after merge, use city**: A group of workers only worked in one firm during the entire period (2010–2015) in *Super-Sociedades* and in *PILA*. As in Criterion 3. We create a new group id, merge by the group id and year, and conclude that a *NIT* corresponds to an *id*. Here, we only drop if *NIT* is not unique, but we do not drop if *id* is not unique. Rather, we compare cities from both sources and keep those with the same reported city. Then we drop if *id* is not unique. Using this criterion, we obtain 79 firms.

14. **Unique group–Unique group but if *id* not unique after merge, use region**: Same as Criterion 13, but using region as the second condition. Using this criterion, we obtain three firms.

15. **Max mode–Max mode but if *id* not unique after merge, use city:** An individual could have had more than one job in either database per year, but there may be one firm in which the worker worked more years (the mode). The number of

years must coincide in both databases. Here, we only drop if *NIT* is not unique, but we do not drop if *id* is not unique. Rather, we compare cities from both sources and keep those with the same reported city. Then we drop if *id* is not unique. Using this criterion, we obtain two firms.

16. **Max mode–Max mode but if *id* not unique after merge, use region:** Same as Criterion 15 but using region second. Using this criterion, we obtain 133 firms.

17. **Repeat 1**: Using the same argument as for Criterion 9, we repeat Criterion 1 iteratively. At this point, we had too little information to repeat Criteria 2–4. Using this criterion, we obtain 149 firms.

### A.6 *PILA*: Employer–Employee panel

To construct the employer–employee panel, we use data from the firms' monthly social security payments reports between January 2008 and December 2008, and data from the match between *Super-Sociedades* and *PILA*. To move from the monthly reports to the annual panel, we proceed in two stages. First, we use the raw data and verify that we always follow the history of a worker that worked at least once in one of the firms in *Super-Sociedades*. We drop observations that have a daily wage[35] below half of the minimum daily wage. In Colombia, in contrast with the United States, workers cannot be hired hourly. Instead, they can have full-time contracts—48 hours per week—or part-time contracts—24 hours per week. Since we do not observe the type of contract—full or part time—we drop observations that have wages below the legal minimum. Following Alvarez et al. (2018), we assign workers to a single firm per month. If a worker has more than one job per month, we assign to the firm with the longest spell. If, after this, there is still more than one firm per worker, we assign the firm with the highest wage. In addition to wage, firm, and worker identifiers, and date, we store the worker's region and city, the firm's registered region and city, the four-digit ISIC codes and aggregate sectors, a dummy, and a variable of whether the worker was on maternity leave. Moreover, using information about tax brackets in Colombia, we construct net wages and total labor per worker.[36]

[35]We construct daily wage as monthly wage to number or reported days.

[36]For income taxes, each year, the government assigns a monetary value in COP to a *Unidad de Valor Tributario*—UVT. During the period of study, the marginal tax rates are the following: 0 if annual wage is below 1,090 UVTs, 19% if annual wage is between 1,090 and 1,700 UVTs, 28% if annual wage is between 1,700 and 4,100 UVTs, and 33% if annual wage is greater than 4,100 UVTs. The exchange rate between COP and UVTs is 27,318.47 COP, approximately 8.5 USD in December 2018. Additional taxes and labor costs could be described as follows: in addition to their wages, a worker receives 12% of her wage in health insurance, 8% in unemployment insurance and an interest of 8% over these, 12% of legal extras, 4% of vacation, and on-the-job risk insurance. In addition, all workers also pay an additional tax of 10% before 2010 and of 208 after that date (*parafiscales*). We use these measures as robustness tests.

Finally we convert all values to real December 2018 USD by first deflating the variables by CPI to remove Colombia's inflation and then using the average COP–USD exchange rate of December 2018, 3,208.263.[37] This avoids including exchange-rate fluctuations in the analysis and US price adjustments.[38]

In the second stage, we move from monthly to annual frequency using two different approaches. First, we use only information for December each year. With this method, we observe year-to-year changes that coincide with the date of the financial reports. Our main specifications use this version. As a robustness check, we aggregate using data from all months and generate monthly averages, following Alvarez et al. (2018). That is, if a worker has more than one job per year, we assign the firm with the longest spell. If, after this, we still have more than one firm per worker, we assign the firm with the highest wage. After using any of the previous alternatives, we construct growth rates of wages, labor costs, and net wages to define job-market transitions. First, we define duration of unemployment as the number of periods that the worker was absent from the database. It is important to recall that being absent on the database does not mean that the worker was unemployed. The worker could have been either unemployed or working in the informal sector. We call this unemployment for simplicity. Second, we define employment status on the previous period. A worker can remain employed (EE) or move from unemployment to employment (UE). Third, we define whether a worker is an entrant to the firm. For this status, we use two alternative measures. The first indicates if a worker started working in the firm in the current period. The second measure of the status tells us that a worker is an entrant if the number of years worked on the firm is below the average number of years worked. In this same, sense we define tenure as the number of years a person has been with a firm. It is important to notice that our measure of tenure is limited by the number of years in the data, 2008–2018. Finally, we define if a worker was rehired by a firm. That is, the worker previously worked in the firm, was hired by another firm for at least one period or absent from the data and then returned to the firm. After measuring the labor-market transitions, we add gender and age to our data. We use an additional appendix of the original *PILA* that includes the individual identifier *personabasicaid*, gender, and date of birth. At this point, we restrict our sample to workers aged between 18 and 60 years in 2008 because 18 is the minimum legal working age in Colombia and 60 is the legal retirement age for males.[39] However, we want to observe the cohort that turned 60 in 2008 until the end of the sample.[40]

[37] We use the CPI index from the Colombian Central Bank reports, and the exchange rate from FRED.

[38] We store each year separately in files called "PILA_monthly_hist_$y$.dta" where $y = \{2008, \ldots, 2018\}$. The code that runs this step is named "PILA_monthly_hist_y.do" and is stored in "PILA Organization."

[39] It is 58 for women.

[40] We store two databases, one for each version of aggregation. The version that uses annual averages is "PILA_workers_annual.dta," the version that uses only December is "PILA_workers_annual_dec.dta." We

### A.7 *PILA*: Firms panel

We create a firms panel about the firms' labor force using the annual version of the workers in *PILA*. Basically, we aggregate the workers' information per firm *id*. We aggregate per date and per date and type of worker: incumbents and entrants. We first create variables containing information about employment and generate total employment of the firm as the total number of workers, entrants, and incumbents. To measure the importance of entrants in the firm, we construct three variables: tenure as the average duration of employment, the proportion of entrants to employment, and entrants to incumbents. Then we move to a block of variables measuring the payroll of the firm. Our main variables are wage bill as the sum of all wages, average wage, standard deviation of log wages, and the 10th, 50th and 90th percentiles of wages per firm to measure changes in the distribution. We create a third block of variables containing demographic characteristics of the workers: age and gender. Since our goal is to measure changes in employment, wages, and ages, we generate for each variable its corresponding version in logs and their log changes. Finally, we construct a block containing firm geographic and sectoral information. We construct a measure of the broad sector using information on the section letter of the ISIC Revision 4 code in the first year that we observe the firm. We define 20 broad sectors following the international standard classification.[41] We create the number of locations, as the total number of different cities that workers report as their city of employment.

## B Appendix: Bootstrap

TO BE COMPLETED

store both files in "PILA/Organization/Output."

[41] Agriculture, Mining, Manufacturing, Electricity, Water Supply, Construction, Wholesale, Transportation, Accommodation, Information, Financial, Real Estate, Professional, Administration, Public, Education, Health, Arts, Other Services, and Extra.

# C Appendix: Empirical Results

**Table 8:** Connected Set of Credit-Supply Shocks: All Firms and Banks Are Connected

| Year | Allocation | Size | Fraction |
|---|---|---|---|
| 2008 | 55,484 | 55,484 | 100% |
| 2009 | 57,145 | 57,145 | 100% |
| 2010 | 49,486 | 49,486 | 100% |
| 2011 | 47,091 | 47,091 | 100% |
| 2012 | 49,965 | 49,965 | 100% |
| 2013 | 51,506 | 51,506 | 100% |
| 2014 | 52,567 | 52,567 | 100% |
| 2015 | 57,021 | 57,021 | 100% |
| 2016 | 58,925 | 58,925 | 100% |
| 2017 | 56,797 | 56,797 | 100% |
| 2018 | 66,399 | 66,399 | 100% |

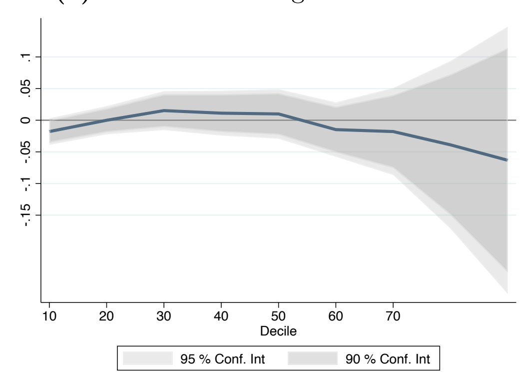
**Table 9:** Summary Statistics: Growth Rates

| | **Mean** | **Std. Dev** | **P95** | **P5** | $N$ |
|---|---|---|---|---|---|
| $\Delta \log(BankingDebt)$ | −0.06 | 1.03 | 1.27 | −1.47 | 17,567 |
| $\Delta \log(Capital)$ | −0.03 | 0.74 | 0.65 | −1.31 | 19,451 |
| $\Delta \log(Wage)$ | 0.02 | 0.25 | 0.34 | −0.30 | 56,875 |

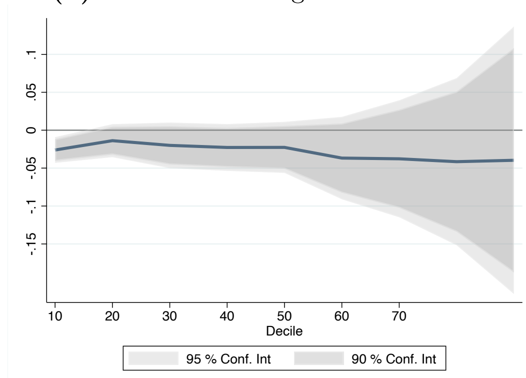
**Note:** Log changes of the main variables of interest: banking debt, capital, employment, and average wages.

**Figure 14:** Effects on Incumbents' and Entrants' Wage Distribution One and Two Years After a Positive Credit-Supply Shock

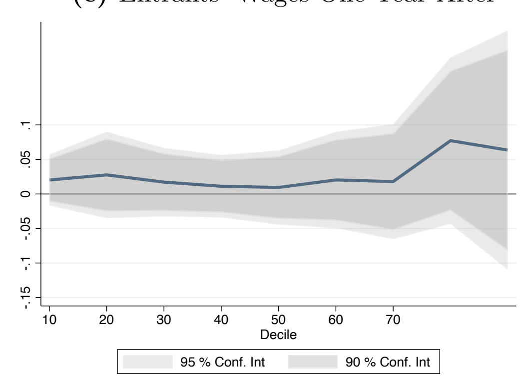
**(a)** Incumbents' Wages One Year After



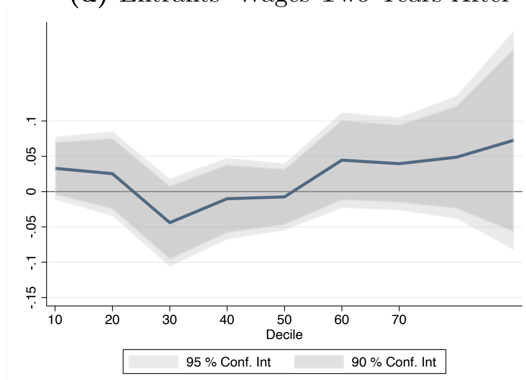

**(b)** Incumbents' Wages Two Years After




**(c)** Entrants' Wages One Year After




**(d)** Entrants' Wages Two Years After




**Note:** Panel **(a)** shows the estimated effect on each income decile for incumbents using equation (7) for $h = 1$. Panel **(b)** estimates it for $h = 2$ Panels **(c)** and **(d)** do the same for entrants. Each regression for incumbents has 1,578,695 observations for $h = 1$ and 1,003,026 for $h = 2$. Each regression for entrants has 453,462 observations for $h = 1$ and 292,513 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the individual and time levels.

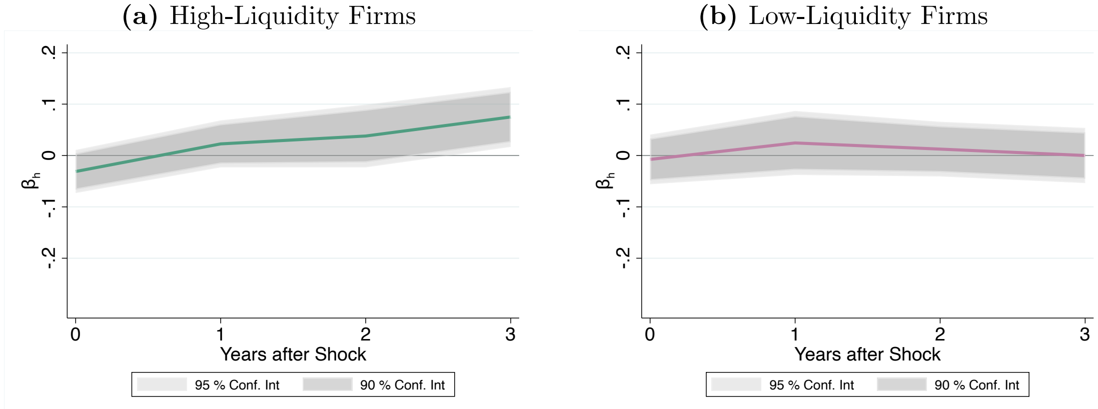
**Table 10:** On Impact Effect of the Credit-Supply Shock on Banking Debt

| | (1) | (2) |
|---|---|---|
| | $\Delta \log(BankingDebt)$ | |
| Credit Shock | 0.17* | 0.18** |
| | (0.07) | (0.07) |
| Sales | | 0.09*** |
| | | (0.02) |
| Locations | | 0.08 |
| | | (0.10) |
| Cash | | 0.37** |
| | | (0.13) |
| Leverage | | −1.97 *** |
| | | (0.21) |
| Firm FE | Yes | Yes |
| Time × Sector FE | Yes | Yes |
| $N$ | 18,957 | 18,920 |

**Note:** Robust Standard errors in parentheses clustered at the firm and time levels. $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$. Estimated effect on banking debt using equation (5) for $h = 0$. We measure banking debt from the financial reports as the ratio of banking debt to total debt.

### C.1 Liquidity

**Figure 15:** Impulse-Response Functions of Average Wages for High- and Low-Liquidity Firms



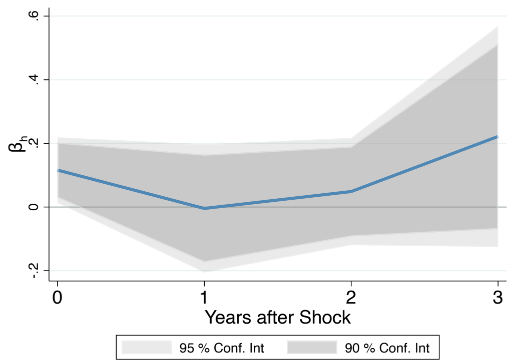

**Note:** Panel **(a)** shows the estimated effect on average wages using equation (5) for high-liquidity firms. Panel **(b)** shows the estimated effect on average wages using equation (5) for low-liquidity firms. A high-liquidity firm is a firm with average cash and short-term investment to assets ratio above the median. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

Figure 15 shows the effect on average wages. The effect is positive and sizable for high-liquidity firms two years after the shock. For a firm with a positive credit-supply shock of one standard deviation, average wages are 1.3% higher three years after the shock. This result is consistent with the expansion of working capital two years after the shock for high-liquidity firms in Figure 7a. We find no evidence of an effect for low-liquidity firms.

## C.2 Additional results

### C.2.1 Large shocks

**Figure 16:** Large Shocks Increase Employment on Impact: Reconciling Our Results With Financial Crises Results in Developed Economies



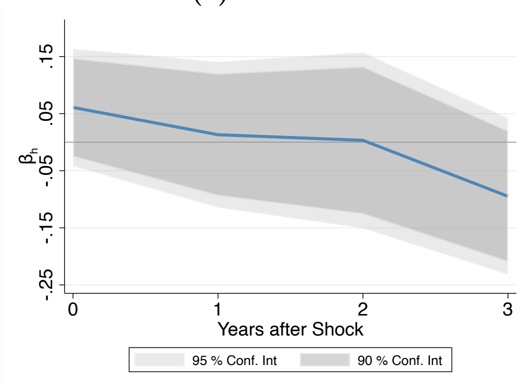

**Note:** Robust standard errors clustered at the firm and time levels. All specifications include as controls lagged log sales, cash, log of number of locations, and demeaned leverage. Sample sizes: $h = 0$: 23,125, $h = 1$: 16,609, $h = 2$: 12,688, $h = 3$: 10,130.

### C.2.2 Incumbents and entrants

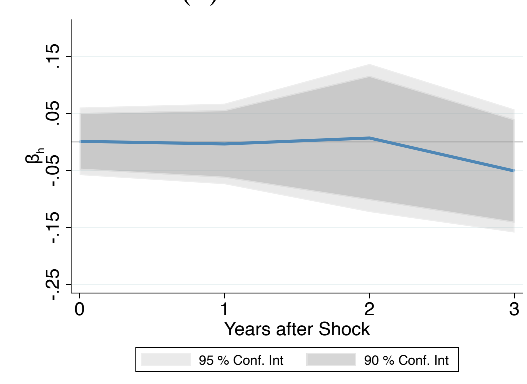
We split our sample between incumbents and entrants. We estimate the effect on employment using equation (5) for each group. Figure 17 shows no differences in the number of entrants compared to incumbents. A compositional effect should imply an increase in the number of entrants and a decline in the number of incumbents. Also, we repeat the exercise on each wage decile using equation (7). Figure 14 earlier shows these results. We recompute the distribution of wages for each group. In the presence of a distributional effect, we would expect differentiated responses in terms of wages for at least one of the two distributions. We find no such different effects between these types of workers.

**Figure 17:** Impulse-Response Functions of Employment for Incumbents and Entrants

**(a)** Entrants




**(b)** Incumbents




**Note:** Panel **(a)** shows the estimated effect on entrants' employment using equation (5). Panel **(b)** shows the estimated effect on incumbents' employment using equation (5). We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

# D Appendix: Model

## D.1 Wages

In this section we derive the wage-setting decision problem. We closely follow the canonical search model in Shimer (2010). Each period, the workers and the firms bargain wages in each of the labor markets: skilled, z, and unskilled u. If the negotiation fails, the workers are unemployed, if it succeeds the workers receive the following wage.

$$\arg\max_{w_n} \tilde{V}(w_n)^{\mu_\mathrm{u}} \tilde{J}(w_n)^{1-\mu_n},$$

where $\mu_\mathrm{u} \in [0, 1]$ is the workers' bargaining power. $\tilde{V_n}(w_n)$ is the marginal benefit of the household for having $\epsilon$ extra workers employed at the current level of consumption and savings receiving wage $w$ instead of $w(s)$. When $\epsilon$ tends to zero,

$$\tilde{V_n}(w_n) = u_1(c, l_\mathrm{z}, l_\mathrm{u})(w - w(s)) + V_n(s, d^h, l_\mathrm{u}, l_\mathrm{z}),$$

where $V_n(s, d^h, l_\mathrm{u}, l_\mathrm{z})$ is the first-order condition of the household problem with respect to labor type $n = \{\mathrm{z}, \mathrm{u}\}$:

$$\tilde{V_n}(s', d'^h, l'_\mathrm{u}, l'_\mathrm{z}) = u_1(c, l_\mathrm{z}, l_\mathrm{u})w(s) + \beta(1 - \rho - p(\theta_n))V_n(s', d'^h, l'_\mathrm{u}, l'_\mathrm{z}).$$

Similarly $\tilde{J_n}(w_n)$ is the value of the firm for hiring $\epsilon$ extra workers at the current firm conditions at wage $w$ instead of $w(s)$. When $\epsilon$ tends to zero,

$$\tilde{J}_n(w_n) = w(s) - w + J_n(s, k, d, m, l_\mathrm{z}, l_\mathrm{u}),$$

where, by the firm's first-order conditions with respect to labor,

$$\begin{aligned} J_n(s, k, d, m, l_\mathrm{z}, l_\mathrm{u}) &= MPL_n - w_n(1 + \theta(r^m - 1) + \lambda_{f1}) + \frac{\zeta_n(1-\rho_n)}{q(\theta_n)} \\ \mathbb{E}M(s')J_n(s', k', d', m', l'_\mathrm{z}, l'_\mathrm{u}) &= \frac{\zeta_n}{q(\theta_n)} \end{aligned}$$

and $MPL_n$ is the marginal product of labor for each of the worker type:

$$\begin{aligned} MPL_\mathrm{u} &= \frac{(1-\mu)\,(1-\mu_r)\, f(k, l_\mathrm{u}, l_\mathrm{z})^{1-\eta}}{l_\mathrm{u}^{1-\eta_r}\left(\mu k^\eta + (1-\mu) l_\mathrm{u}^\eta\right)^{1-\frac{\eta}{\eta_r}}} \\ MPL_\mathrm{z} &= \left(\frac{f(k, l_\mathrm{u}, l_\mathrm{z})}{l_\mathrm{z}}\right)^{1-\eta}. \end{aligned}$$

The solution of the Nash bargaining problem is then

$$\mu_n u_1(c, l_\mathrm{z}, l_\mathrm{u}) J_n(s, k, d, m, l_\mathrm{z}, l_\mathrm{u}) = (1-\mu_n) V_n(s, d^h, l_\mathrm{z}, l_\mathrm{u})$$

To solve for wages, we plug the solution of the Nash equilibrium problem into the household's first-order conditions for labor to write them as function of $J_n(s, k, d, m, l_\mathrm{z}, l_\mathrm{u})$ and $J_n(s', k', d', m', l'_\mathrm{z}, l'_\mathrm{u})$. Then we use the firms' first-order conditions for labor to solve for wages in terms of parameters, labor, and market tightness:

$$\begin{aligned} w_\mathrm{u} &= \left(\mu_\mathrm{u} MPL_\mathrm{u} + \mu_\mathrm{u}\zeta_\mathrm{u}\theta_\mathrm{u} + \frac{(1-\mu)\phi l_\mathrm{u}^{(\nu-1)}}{u_1(c, l_\mathrm{z}, l_\mathrm{u})}\right) \times \frac{1}{1 + \mu_\mathrm{z}(R^m - 1 + \lambda_{f1})\theta} \\ w_\mathrm{z} &= \left(\mu_\mathrm{z} MPL_\mathrm{z} + \mu_\mathrm{z}\zeta_\mathrm{z}\theta_\mathrm{z} + \frac{(1-\mu)\phi l_\mathrm{z}^{(\nu-1)}}{u_1(c, l_\mathrm{z}, l_\mathrm{u})}\right) \times \frac{1}{1 + \mu_\mathrm{z}(R^m - 1 + \lambda_{f1})\theta}. \end{aligned}$$

## D.2 Calibration

**Table 11:** Summary Statistics: Credit Supply Shock

| | (1) Banking Shock |
|---|---|
| Banking Shock$_{t-1}$ | 0.37*** |
| | (0.12) |
| Constant | −0.01 |
| | (0.02) |
| $N$ | 135 |

**Note:** Robust Standard errors in parentheses clustered at the firm and time levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

**Table 12:** Summary Statistics: Interest-Rate Calibration

| | **Mean** | **Std. Dev** | **P95** | **P5** | $N$ |
|---|---|---|---|---|---|
| $R^m$ | 1.03 | 0.03 | 1.08 | 0.98 | 574 |
| $1/\beta$ | 1.09 | 0.03 | 1.15 | 1.04 | 574 |
| $R$ | 1.08 | 0.03 | 1.15 | 1.04 | 574 |

**Table 13:** Summary Statistics: Firm Parameters

| | **Mean** | **Std. Dev** | **P95** | **P5** | $N$ |
|---|---|---|---|---|---|
| $\delta$ data | 0.16 | 0.19 | | | |
| $\delta$ PWT | 0.04 | 0.00 | 0.04 | 0.04 | 10 |

## D.3 Results

**Figure 18:** Impulse-Response Function of the Credit-Supply Shock

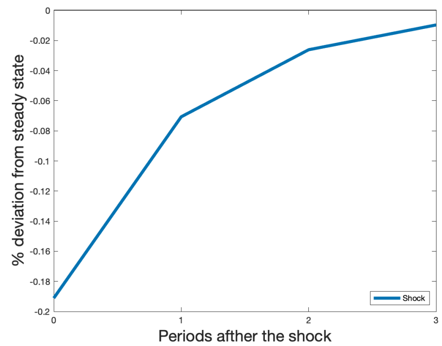
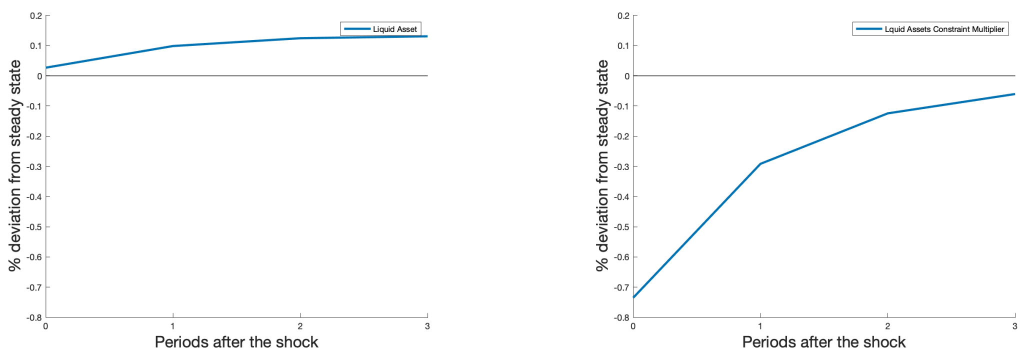



**Figure 19:** Impulse-Response Functions for Liquid-Asset Holdings and Borrowing Interest Rate to a Positive Credit-Supply Shock

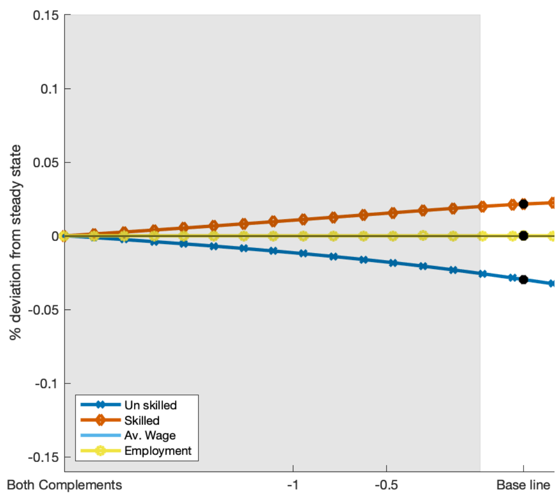
**(a)** Liquid Assets **(b)** Borrowing Interest Rate



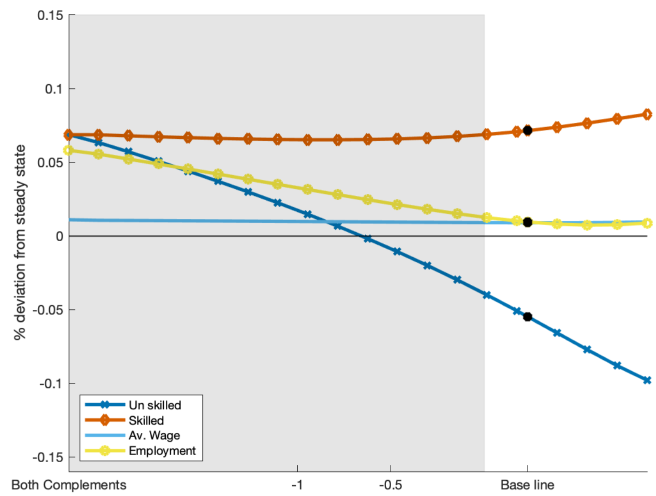

**Note:** Impulse-response functions for the baseline model simulations.

**Figure 20:** Sensitivity Analysis of the Labor-Market Outcomes to the Substitution Parameter Between Capital and Low-Skilled Workers $\eta_r$

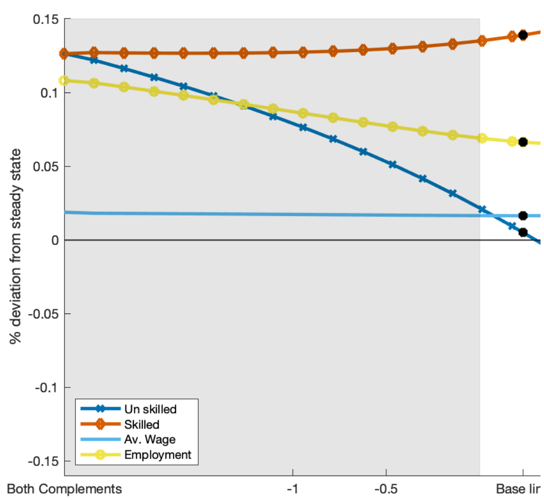
**(a)** $h = 0$




**(b)** $h = 1$




**(c)** $h = 2$




**(d)** $h = 3$

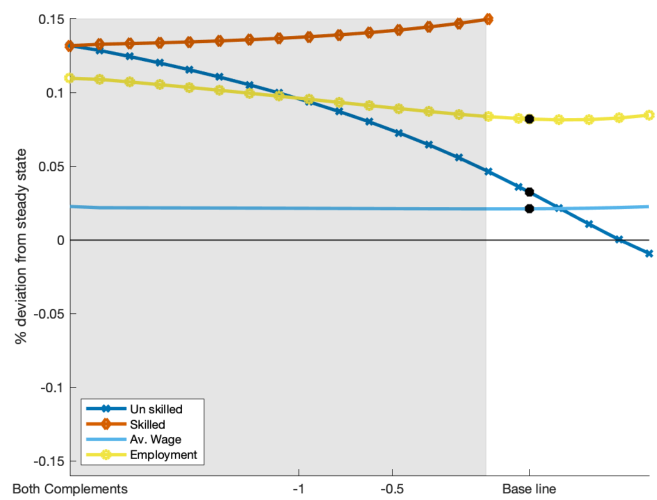
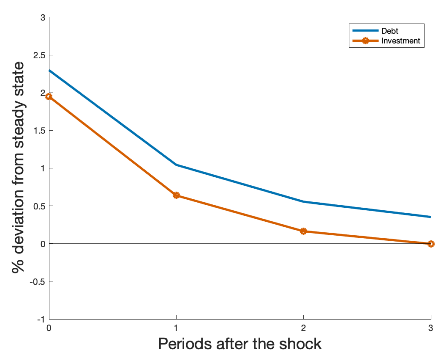


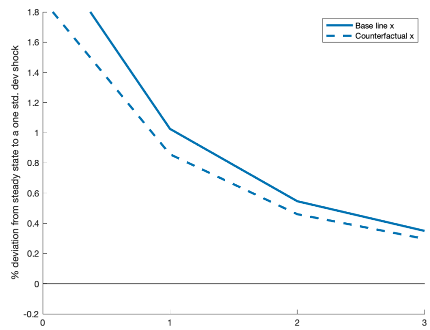
**Figure 21:** Impulse-Response Functions of Unconstrained Firms' Debt and Capital to the Credit-Supply Shock



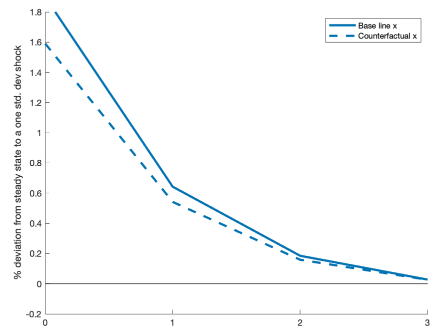
## D.4 Counterfactual

**Figure 22:** Comparing the Impulse-Response Functions on Debt, Investment, and Liquid Assets to a Positive Credit-Supply Shock for Different Levels of $\bar{\tau}$

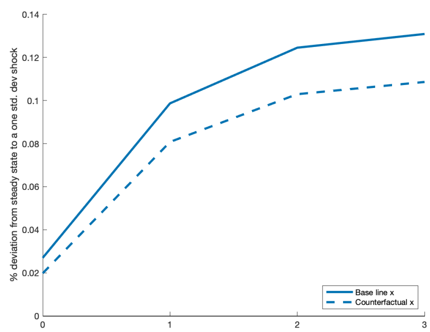
**(a)** Debt



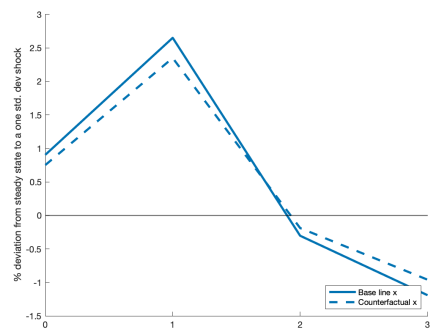

**(b)** Investment




**(c)** Liquid Assets




**(d)** Liquid Assets Lagrange Multiplier




**Note:** Impulse-response functions to the model without working capital.