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 administrative data in Colombia between 2008 and 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 for explaining the results: capital-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, there is 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.[1] 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, we find that 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 positions. We develop a model of financial frictions and labor markets to study the mechanisms and the aggregate effects.

The direction of the effect of a change in access to corporate credit on employment and wages is 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.[2] 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] See for example 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).

[2] Firms with either sales or assets of more than 20000 times the legal minimum wage are obligated to report, that is firms with assets or sales of around \$4.11 USD million annualy. The average minimum wage in Colombia during the period was \$205.8 USD, using the Dec 2018 $COP/USD = 3{,}208.263$

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 using the firm's financial reports and the employer-employee data, we 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 differs from the existing literature that finds that during large credit contractions employment substantially decreases (Chodorow-Reich, 2014; Huber, 2018).

Second, we study heterogeneous effects across the distribution of wages. We estimate quantile regressions at the worker-level (Firpo et al., 2007) to estimate the effect on each decile of wages. We find that there is 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 during normal times a credit expansion increases wage dispersion, 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 positions. We find that 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, there are heterogeneous responses in terms of labor demand and working capital. High liquidity firms not only increase their capital stock, but increase employment. In contrast, firms with low liquidity reduce their working capital by 1.3%. Wages at the bottom of the distribution fall by 10% in firms with low liquidity, and 5% in firms with high liquidity.

We interpret our results as follows. A positive credit supply shock creates an investment opportunity. If the firm does not face a liquidity constraint, the firm is be able to expand in scale. Labor demand will change differentially for all types of workers but it increases overall. Thus, we observe an increase in employment. However, if the firm does not have enough internal resources to simultaneously increase capital and hire more of all types of workers, the firm will reduce demand for those workers that are better substitutes for 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 and 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 findings in terms of aggregate employment and the existing literature on financial crises. We can interpret financial crises as circumstances in which firms are extremely constrained in terms of liquidity. As a result employment decreases.[3]

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 similar to 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 in the presence of both mechanisms - liquidity constraints and a capital-low-skill substitutability production structure - a positive credit supply shock reduces low-skilled wages over a three year horizon. 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, in the absence of liquidity constraints low income wages slightly decline, while high income wages increase relative to constrained firms. When the production structure only uses one type of labor, we find a small reduction on wages one period after the shock, and a significant increase after. Thus, the presence of both mechanisms is necessary to describe the patterns that we observe 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 on bank deposits and the borrowing rate - influence firms' response to credit supply shocks. We find that when the intermediation premium decreases by 20%, low income workers do not lose as much as in the baseline model. In particular, we find that one year after a positive credit supply shock low-skilled wages are 5% higher

[3] In the additional results in the appendix, we find that when we restrict our sample to large shocks - more than one standard deviation - we find that a positive credit supply shocks has a positive and significant effect on employment.

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 a whole faces lower interest borrowing rates the 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 firms with low liquidity 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.

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) shows using an instrumental variable approach that during the global financial crisis, employment in firms with banking relationships with more affected banks were 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 the education level and the type of contract. We contribute to this literature in two key dimensions. First, we study the effect on 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 is that we find 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 it is related to the literature on financial shocks and firms dynamics (Amiti and Weinstein, 2018; Jiménez et al., 2019; Gilchrist et al., 2017; Kim, 2018). Methodologically, our paper closely follows Amiti and Weinstein (2018).[4] The methodology consists of identifying credit supply shocks through bank-firm relationships using bank and firms 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 perspectives. We study the effect of credit shocks and

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

liquidity in 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-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 we are the first paper that studies how corporate credit supply shocks affect wages from the firm perspective. We 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 to the standard approach of a small open economy with working capital three dimensions: 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, and 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 *Super Intendencia Financiera*. Colombian banks and credit institutions are obligated to report every quarter the balance of all their credit operations (*Formato 341*). This information allows us to track the total amount of lending from a bank b to the firm f since the first period of the credit until its maturity. We restrict our data to credits 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[5], with total initial

[5] First observation corresponds to the initial date, last observation corresponds to final credit date.

debt above $10000 COP (around $3 USD), and with interest rate below the legal maximum rate of the period (33.51% 2017-1). In addition, we restrict our sample to banks with more than 3 years of data and to banks with more than five relationships. Then, to aggregate the data at the firm-level, for every bank-firm we keep the debt stock in the fourth quarter. See data Appendix A.1 for more details about the data organization process. Our final sample has 138,683 firms and 16 banks.[6] We also use banks financial statements from *Super Intendencia Financiera*. These are monthly reports, and all the data is publicly available. See appendix A.1 for more details.

At the firm-level, we use financial reports and their corresponding appendices from *Super Intendencia de Sociedades*, the government agency in charge of overseeing corporations. Firms with either sales or assets of more than 20,000 times the legal minimum wage (about $4.11 annual million dollars per year) are obligated to report.[7] We use the annual reports from 2008-2015.[8] We 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.

One of the contributions of our paper is the ability to link banks corporate credit reports with the firms' financial statements to workers employment history. That is, we link the credit reports -*Formato 341*- with the financial reports -*Super Sociedades*-, and with the social security payment reports -*PILA*. Colombia uses an official unique identifier for each corporation and one 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 EIN number in the US -*Employer identification number*-. The individuals' unique identifier is called *cédula*, and it is comparable to the SSN -*Social security number* - in the US. To link the credit reports and the financial statements we use the banks' and firms' *NIT*'s. Both data sources use the national unique firm identifier *NIT* to keep track of banks and firms. 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 develop a merging algorithm where we create a one to one

[6] 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

[7] The average minimum wage in Colombia during the period was $205.8 USD, using the Dec 2018 $COP/USD = 3208.263$

[8] The reason why we restrict our financial reports to 2015 is because on this year firms in Colombia started a transition between the domestic accounting system -PUC- to the international standards -NIIF-. Therefore, reports from the subsequent years have some structural differences and incompatibilities, being the first that this transition has been realized in different stages. Some firms, in years 2016-2018 submitted their reports in the PUC system while some in the NIIF system.

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 employers-employee. 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 each worker based on the their basic monthly wage. We drop observations that have a daily wage below half of the minimum daily wage. We construct daily wage as monthly wage to number of reported days.[9] 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.[10] Due to concerns of seasonality, 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 average monthly Colombian CPI with base December 2018 and the exchange rate COP/$US in december 2018.

Our final sample contains 10,835 firms and 3,321,640 workers. Our sample corresponds to large financial firms in Colombia,[11] 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 U.S. In terms of wages, on average, our firms pay lower wages than the U.S firms, but higher wages compared to the Colombian market. For instance, the average wage in our sample is $542.96 dollars per month, around 2 times the average minimum wage during the sample period.[12]

[9]In Colombia, in contrast to the U.S, workers can not be hired hourly. Instead, they can have full time contracts - 48 hours per week- or part time contracts - 24 hours per week.

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

[11]We exclude from our sample firms in the public sector, electricity, and water supply. We include firms in real estate and financial sector that are not credit issuers, and that are not publicly traded. This means, that they are not part of the banks sample.

[12]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

Table 1: Summary Statistics

	Mean	**Std. Dev**	**P95**	**P5**	N
			Firms		
Employment	121	526	429	3	10835
Leverage	0.38	5.41	0.73	0.02	10835
Equity to Assets	3.62	86.16	8.28	1.17	10835
Capital	16.24	222.11	42.79	0.15	10835
Sales	10.96	141.50	32.69	0.22	10835
Banking Shock	0.05	0.13	0.27	-0.12	10835
			Workers		
Wage	542.96	625.46	1683.68	166.71	3321640
Age	34.83	10.32	54.00	21.00	3321640
Male	0.59	0.49	1.00	0.00	3321640

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

3 Identifying Shocks to Credit Supply

To identify shocks to credit supply at the firm-level, we closely follow Amiti and Weinstein (2018) (AW). This framework, identifies credit supply shocks as the firms' common change in borrowing coming from a particular bank. In other words, we measure the firm-bank pair variation in borrowing that is 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 banks fixed effects. To be concrete, suppose that 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 (α_{ft}), a shift in bank b's lending to all firms (β_{bt}), or forces idiosyncratic to firm f and bank b (ϵ_{fbt}). This situation can be 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 β_{bt}. Also, the estimation procedure allows for creation and termination of credit relationships.[13], and it is possible to aggregate at the firm-level keeping a reasonable eco-

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

nomic interpretation of the shocks.

To allow for the creation and destruction of bank-firm relationships and to give an economic interpretation, we re-normalize 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 coefficients and we aggregate them at the firm-level to define a credit supply shock.[14] We use as weights the importance of each bank b in firm's f debt in period $t-1$:

$$\theta_{fbt} = \frac{d_{fbt-1}}{\sum_b d_{fbt-1}} \tag{4}$$

We define a credit supply shock as follows:

$$\text{Supply Shock}_{ft} = \sum_b \theta_{fbt-1} \hat{\tilde{\beta}}_{bt} \tag{5}$$

We interpret the credit supply shock as the percentage change in loan supply to firm f relative to the average change in credit supply. That is, as idiosyncratic changes of 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 to sufficient overlap between banks and firms. That is, we require a set of banks and firms that are connected to each other. If a bank only lends to one firm, it is not possible to identify if changes in debt are coming from the bank or from

[14] AW show that the following moment condition -Equivalent to equation 8 in AW-

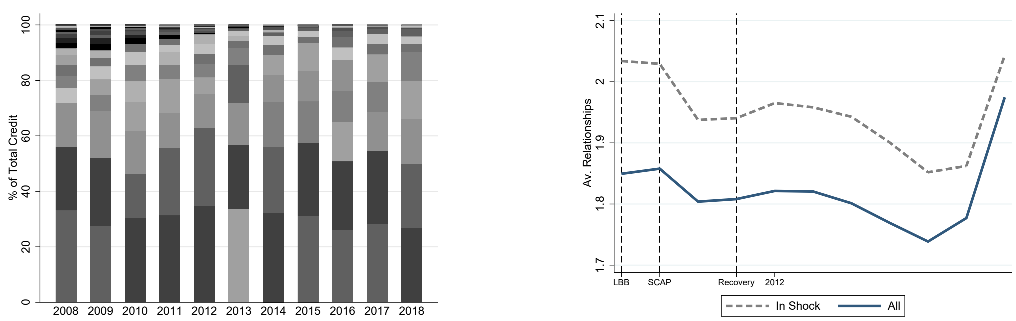
$$\Delta d_{ft} = \hat{c}_t + \hat{\tilde{\alpha}}_{ft} + \sum_b \theta_{fbt-1} \hat{\tilde{\beta}}_{bt} \tag{3}$$

captures the total change in borrowing of firm f, including old and new borrowing, that exactly matches the firm loan growth rates.

the firm. Similarly, an equivalent situation will happen 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 to have a large set of banks, in which the presence of all banks and firms is non negligible but one bank can not 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 are negligible, 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 within the group of banks, there are two banks that have 40% of the credit portfolio -Bancolombia and Banco de Bogotá- which guarantees the relevance of some of the banks in the market, without being completely dominant. Similarly, Panel B shows that on average, firms have more than one relationship over time. We want to highlight that the structure of the credit reports presents an ideal setting to estimate these idiosyncratic credit supply shocks.

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 per bank in our sample. We compute corporate credit as total credit issued by bank firm to all firms in the first quarter per 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, and the dotted line shows the average number of relationships of firms with more than four consecutive periods in the sample.

Using the credit data, we estimate equation 2 and validate our results with the cross-section of the banks. We use the banks' publicly available financial reports and merge them with our estimates of the credit supply shocks. Appendix A.2 contains the details of the data organization process.[15]

We first verify that the $\hat{\hat{\beta}}_{bt}$ is positively correlated with the percentage change of commercial credit reported from the banks' balance sheets. We estimate $\hat{\hat{\beta}}_{bt}$ using Δd_{Zt} from the credit reports. We expect our estimate $\hat{\hat{\beta}}_{bt}$ to be correlated with the percentage change in lending Δd_{bt} from the banks' balance sheets. Since the change in lending is an equi-

[15] Table 8 in the Appendix shows that all firms and banks are connected.

librium object, we expect the correlation between $\hat{\hat{\beta}}_{bt}$ and Δd_{bt} from the balance sheet to be positive and statistically significant, but different from one. 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 the 99% level.

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. Even though our methodology does not take a stand in the interpretation or the economic nature of the credit supply shock, we can think of situations that increase credit supply. For example, banking marketing activities that increase the number of deposits, or extra returns in some investments different from 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[16] since most of the 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 to the registered capital of the bank. We expect a negative sign between our measure of capital adequacy and the credit supply shock. Columns 3-4 on 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, what we do is measure change in credit coming from the bank that is different from the aggregate component. However, since we estimate the shock year by year, we might be concerned that there is some anticipation of the shocks or that there are 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 HP filter on impact, one period before and one period forward. From these results, there are two important conclusions. First, there is a small but statistically sig-

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

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 α_t are time fixed effects. Robust standard errors in parentheses clustered at the bank level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

nificant autoregressive component on the shocks. That is, some banks 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.[17]

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 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.

[17] Given that there is some persistence of the shock, we verify our firm-level, and worker-level results only suing the residuals of the estimates in Column 1 of Table 3. Our results are robust to this change. However, we preferred the original specification to keep 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 GDP$_{t-1}$			-0.02	
			(0.91)	
Cyclical component 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 smooth 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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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 the response of wages 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 the following equation:

$$\log Y_{ft+h} - \log Y_{ft-1} = \beta_{0h} + \beta_h \,\text{Supply Shock}_{ft} + X_{ft-1}\Gamma_h + \alpha_{jth} + \alpha_{fh} + \epsilon_{fth} \tag{6}$$

where, Y_{ft+h} is a firm-level outcome of interest (investment, employment, and wages), α_{jth} are sector-time fixed effects, α_f are firm effects, and X_{ft-1} is a set of firm-level controls. Our coefficient of interest is β_h that measures the cumulative change in Y_{ft+h} to a one unit increase of the credit supply shock relative to the median shock h years after the shock. This is a Jordá projection (Jordà, 2005). Since 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 5 as our measure of the credit supply shock.[18] Our set of controls includes firm size in terms of sales and number of locations, liquid assets holdings to total assets[19], and demeaned leverage. Our set of controls is 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 level. We 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 follows:

$$\begin{aligned}\log(w_{ift+h}) - \log(w_{ift-1}) = &\beta_h \,\text{Supply Shock}_{ft} \\ &+ \beta_{hd} \,\text{Supply Shock}_{ft} \times decile_{it-1} + X_{ift-1}\Gamma_h + \alpha_{fth} + \alpha_{ih} + \epsilon_{ifth}\end{aligned} \tag{7}$$

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

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

$$p\Big(\log(w_{ift+h})\Big) = \beta_0 + \beta_s \,\text{Supply Shock}_{ft} + X_{ift-1}\Gamma + \alpha_{fth} + \alpha_i + \epsilon_{ifth} \tag{8}$$

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 on impact, one year, two, and three years after the shock, that is $h = \{0, 1, 2, 3\}$.

4.2 How credit supply affects investment, employment and wages

First, we establish that there is a positive effect of the credit supply shock on banking debt. We measure a firm's banking debt as the total debt debt from all domestic banks using data from the firms' financial reports. Figure 2a shows that the effect of a positive credit supply shock on banking debt is significant with a confidence interval of 95% on impact, and goes

[18] Since we use estimated regressors we compute our standard errors using a bootstrap

[19] We understand by liquid assets holdings cash and short-term investments

to zero after that. Table 10 shows the impact effect without firm-level controls. There are two points that we want to highlight. First, we consider this fact as a proof of concept of 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% (0.18×0.13). Given that the average growth rate of banking debt is -6%, this is a sizable effect.[20]

Figure 2b shows the effect on gross investment. We find that a positive credit supply shocks causes gross investment to increase on impact[21]. 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 of time.[22] In terms of magnitude, the size is again quite large. On average, the firms in our sample have decrease the capital stock of 3% per year, and the effect of a one standard deviation shock is 1.8%. (See Tables 9 and 11 in the Appendix). The effect on debt is smaller than the effect in the capital stock. If the average firm receives a one standard deviation credit supply shock, the capital stock increases by 0.29 million dollars while debt increases by 0.15 million dollars. This implies that the firm needs to raise funds from other resources, like cash.

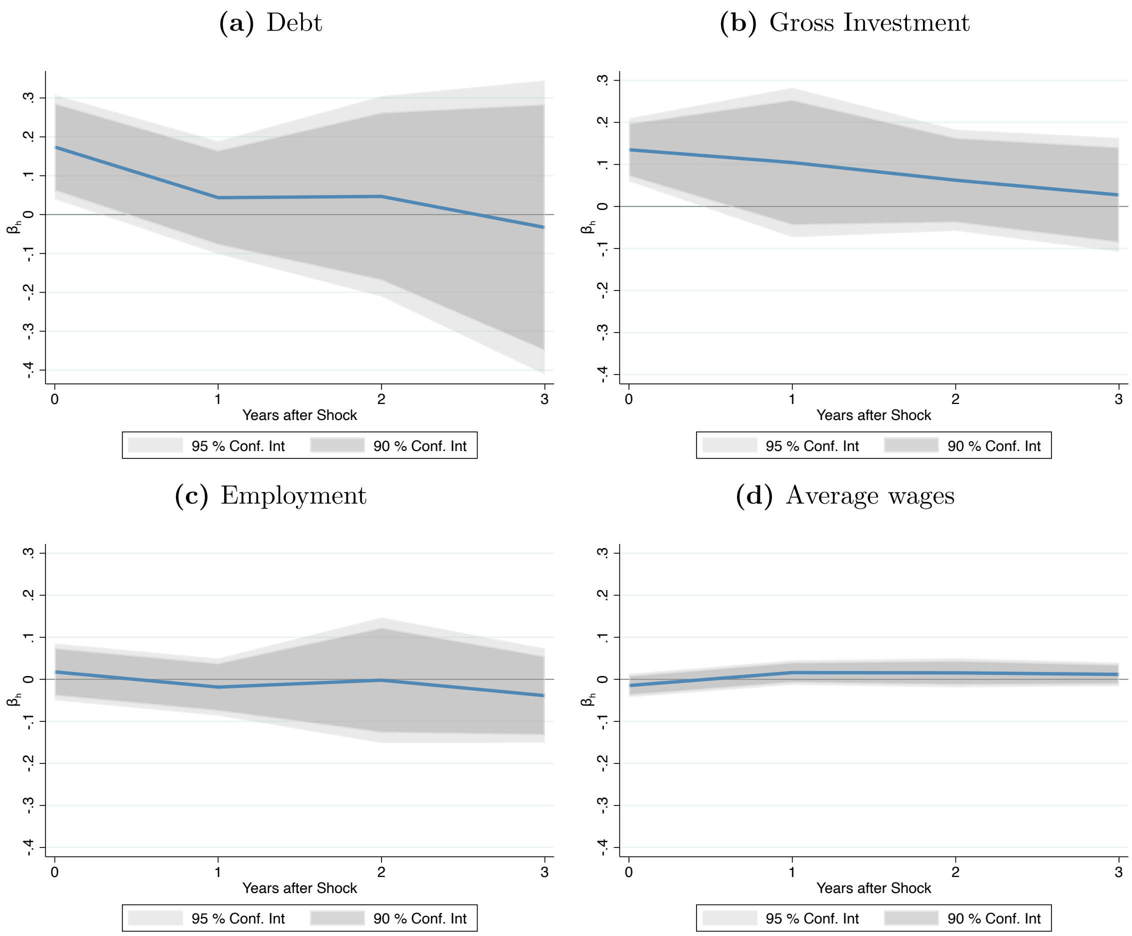
We now turn into the effects of the credit supply shock on labor market outcomes. We do not find a significant effect on employment or average wages. Figure 2c shows the impulse response function for employment and Figure 2d for wages. From the graphs we can not only conclude that the effect is not statistically significant, but its magnitude is also small. This result is quite surprising in terms compared with previous findings on employment changes during financial crisis. 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

[20]Table 9 in the Appendix shows the summary statistics of the one year growth rates of the main variables of interest.

[21]Measured as change in the physical capital

[22] This result differs from Amiti and Weinstein (2018). They find that a positive credit supply shock leads on average to a reduction on investment for firms that do not rely on loans as a main source of financing. As the loan to assets portfolio increases, the effect of a positive credit supply shock becomes negative. One way to reconcile our results from 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 substitute for financing. In our sample, most of our firms are non-listed firms. Therefore, our result is in line with the positive result of firms that heavily rely on debt.

Figure 2: Impulse response functions of a positive credit supply shock on banking debt and gross investment



Note: Panel **(a)** shows the estimated effect of a positive credit supply shock on banking debt using equation 6. We measure banking debt from the financial reports as total debt from domestic banks. Panel **(b)** shows the effect on the change of the capital stock. **(c)** shows the estimated effect of a positive credit supply shock on employment using equation 6. We measure employment as the total number of workers. Panel **(d)** shows the effect on average wage. We interpret the change in capital as gross investment. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time level.

closest scenario to a financial crises, a period with a large volatility of credit supply. Figure 15 in the appendix shows that there is 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

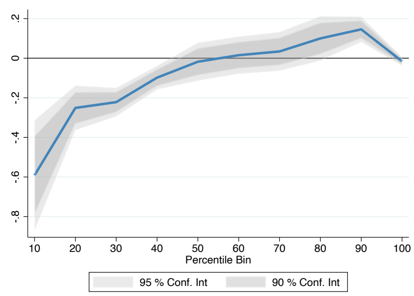
We exploit the worker-level variation to estimate the impact of the corporate credit supply shocks on the distribution of workers or distribution of wages across workers.. First we study the effect on the growth rate of wages per decile, and second we study the level effect on the distribution of wages. To estimate the effect on wage growth, as described in equation 7, we classify each worker in a wage decile. The first decile of income includes workers with the lowest wages, while the tenth decile represents the top of the wage distribution. The coefficients of interest is the sum between the average effect and the interaction term between the shock and each decile. We interpret the result as the total effect on each decile of wage.

Figure 3a shows the effect on impact while Figure 3b shows the effects one year after the shock. The horizontal axis shows each of the wage bins. For example, 10 represents workers between the 0-10 the percentile, 20 is the group between 10-20, and so on. The vertical axis shows the estimated coefficients of the total effect of a positive credit supply shock in the growth rate of wages. On impact, there is a negative and 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.

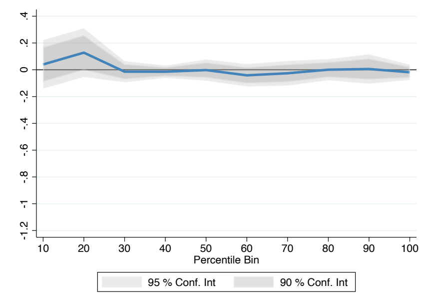
We establish that there is a temporary effect on the growth rate of wages. Now, we turn our attention not to the effect on each of the workers, but on the level of income. That is, in the cut-off values of each decile of income. Here we want to understand the effect of a credit supply shock on the distribution. To do so, we estimate equation 7. Figure 4 establishes one of the main empirical result of the paper. This time, the horizontal axis represents the cut-off value of each percentile of income. The vertical axis shows the estimated coefficients. This exercise is important in the following way. Before we were comparing changes in wages of each of the groups of workers. Now, we study how the distribution changed, This allows for a recomposition of each decile. The result shows that there is a negative effect on below

Figure 3: A positive credit supply shock reduces wages in the bottom half of the wages distribution while increasing wages at the top of the distribution

(a) Wages on impact



(b) Wages one year after



Note: Panel **(a)** shows the estimated effect of a positive credit supply shock on each decile bin using equation 7 for $h = 0$. Each point on the horizontal axis represent a decile of income from the lowest bound of the decile to the upper bound. For example, 10 are workers between 0-10 percentile of income. Panel **(b)** estimates it 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 level.

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 a more permanent effect on overall 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 a 95% confidence interval 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.[23]

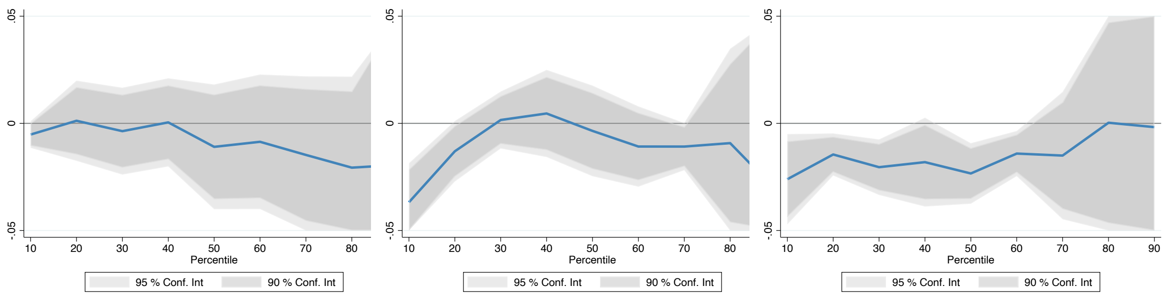
We interpret positive effect of credit supply shock on the capital stock and and the negative effect on the bottom half of the distribution as evidence of capital-skill substitutability. There is considerable evidence of the substitutability between capital and routine workers in developed countries (Vom Lehn, 2020; Lafortune et al., 2019; Alvarez-Cuadrado et al., 2018; Acemoglu and Autor, 2011).[24] In this sense, a credit supply shock generates an in-

[23] To our knowledge we are the first ones to estimate the heterogeneous effect of a credit supply shock along the distribution of wages. Moser et al. (2021) is the closest paper to ours. They 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 within firm inequality, but decreases between firm inequality. We differ from them in two dimensions. Firs, our shock is not an aggregate shock. Instead we capture changes to credit supply that are idiosyncratic to the banks. That is, we abstract from the business cycle. Second, we do not study within and between firm inequality. Our decile estimates capture the effect in the overall distribution of wages

[24] 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

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 8 for $h = 0$. Panel **(b)** estimates it for $h = 1$ and Panel **(c)** for $h = 2$. The horizontal axis shows the cut-off value of each of the correspoding percentiles. Each regression has 6150523 observations for $h = 0$, 2976639 for $h = 1$, and 1879977 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time level.

vestment opportunity, and in order to take all advantage of the opportunity firms reduce labor demand for the type of workers that are substitutes to capital.

4.4 Uneven effect across firms: Liquidity constraints

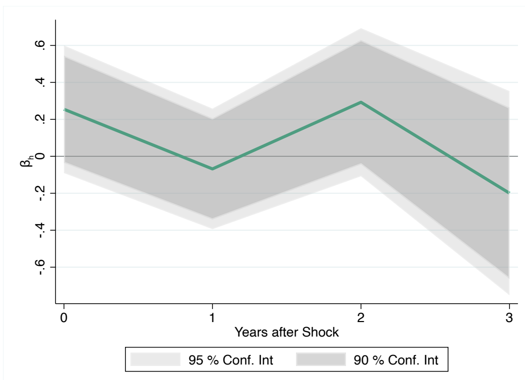
We establish that a positive credit supply shock creates an investment opportunity in terms of physical capital. Simultaneously, there is a negative effect on the bottom half of the wage distribution. But, if these firms face an investment opportunity, why does demand increase for some types of workers and not for others? One potential explanation is the role played by liquidity. Gilchrist et al. (2017), for example, find that the liquidity channel is important for 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 adjust their demand for labor when they increase their capital stock. In this section, we study heterogeneous responses of firms with different levels of liquidity to a positive credit supply shock.

We split our sample between firms with high liquidity and firms with low liquidity. A firm with high liquidity is a firm whose average cash and short-term investment holdings to assets ratio is above the median. Figure 5 compares the effect on debt and gross investment between high and low liquidity firms. There is no significant difference in the response between the two types of firms. We interpret this result as evidence that a positive credit supply shock creates an investment opportunity that is similar to all types of firms and is not affected by firm level liquidity.

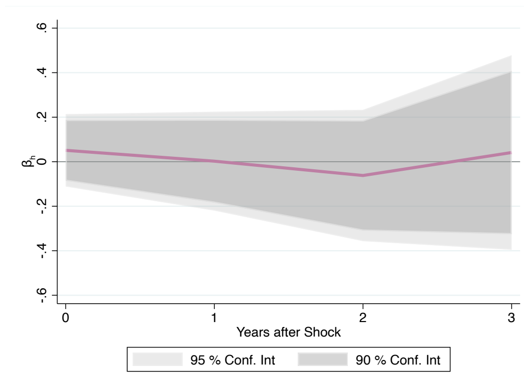
also a characteristic of the Colombian labor market.

Figure 5: Impulse response functions to a positive credit supply shock on debt and gross investment of firms with different levels of liquidity

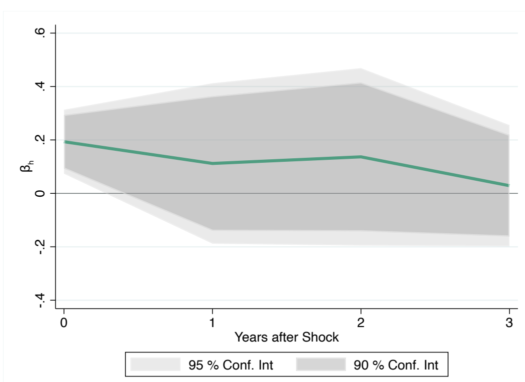
(a) Debt: firms with high liquidity



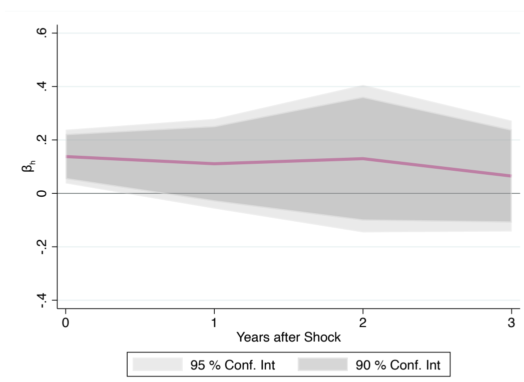
(b) Debt: firms with low liquidity



(c) Gross Investment: firms with high liquidity



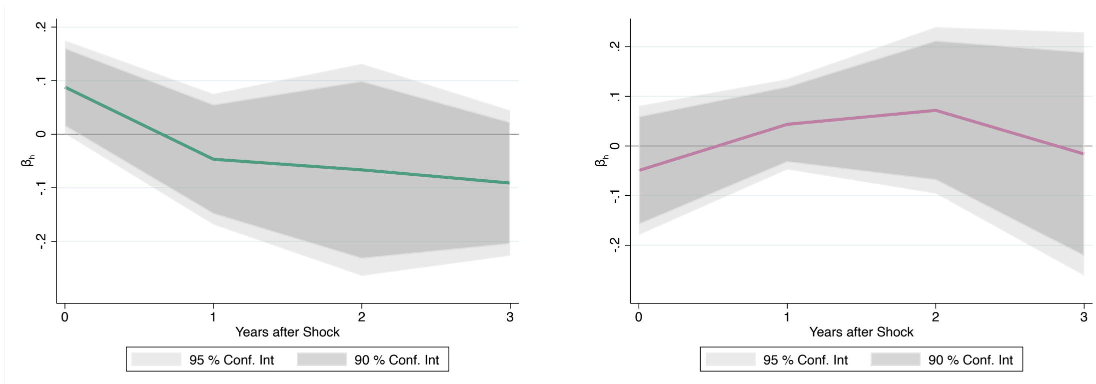
(d) Debt: firms with low liquidity



Note: Panels **(a)** and **(c)** show the estimated effect of a positive credit supply shock on banking debt and gross investment using equation 6 for high-liquidity firms. Panels **(b)** and **(d)** show the estimated effect on banking debt and gross investment using equation 6 for low-liquidity firms. A high liquidity firm is a firm with average cash and show 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 level.

Figure 6: Impulse response functions to a positive credit supply shock on employment of firms with different levels of liquidity

(a) High liquidity firms **(b)** Low liquidity firms

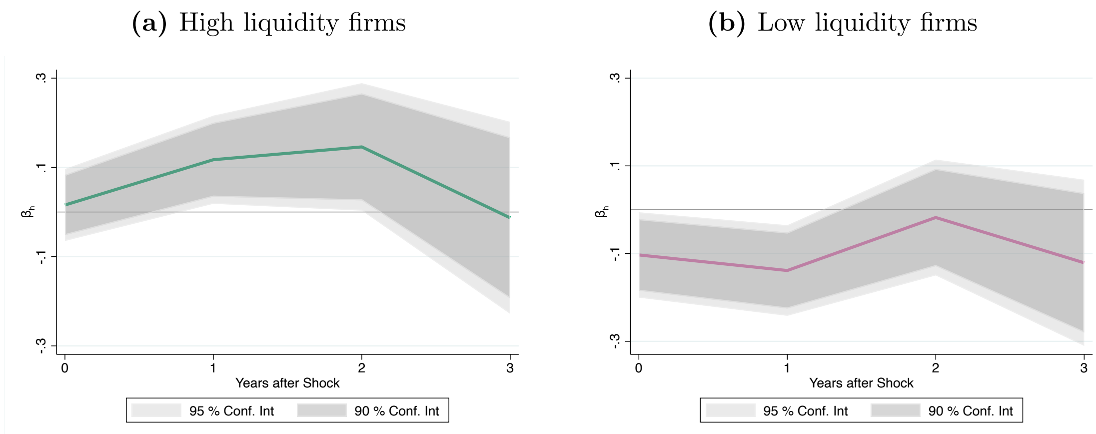


Note: Panels **(a)** shows the estimated effect of a positive credit supply shock on employment using equation 6 for high-liquidity firms. Panels **(b)** and **(d)** shows the estimated effect on employment using equation 6 for low-liquidity firms. A high liquidity firm is a firm with average cash and 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 level.

In the presence of working capital constraints financed with liquid funds and a neoclassical production function where capital and labor are complements, we should expect that firms with more cash holdings - those that are less financially constrained - could increase their labor demand more than financially-constrained firms. In terms of employment, the first two panels of figure 6 compare the effects between firms with high liquidity and firms with low liquidity. The effect of a positive credit supply shock is positive and statistically significant for firms with high liquidity. The point estimate for firms with low liquidity is negative and non significant. This suggests that one interpretation 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 with higher labor demand if the firm has enough internal resources to finance an expansion in scale. Otherwise, labor demand decreases.

Figure 7 compares the effect on working capital between firms with high liquidity and firms with low liquidity. We measure working capital as the ratio of short-term assets to short-term liabilities. This measure compares the amount of liquid funds with firm's the current obligations. In response to a positive credit supply shock firms with low liquidity reduce their working capital on impact and it remains low one year after the shock. In contrast, the effect on working capital for firms with high liquidity is positive and statistically

Figure 7: Impulse response functions to a positive credit supply shock on working capital of firms with different levels of liquidity



Note: Panel **(a)** shows the estimated effect of a positive credit supply shock on working capital using equation 6 for high-liquidity firms. Panel **(b)** shows the estimated effect on working capital using equation 6 for low-liquidity firms. We measure working capital as the current assets to current liabilities ratio. 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 level.

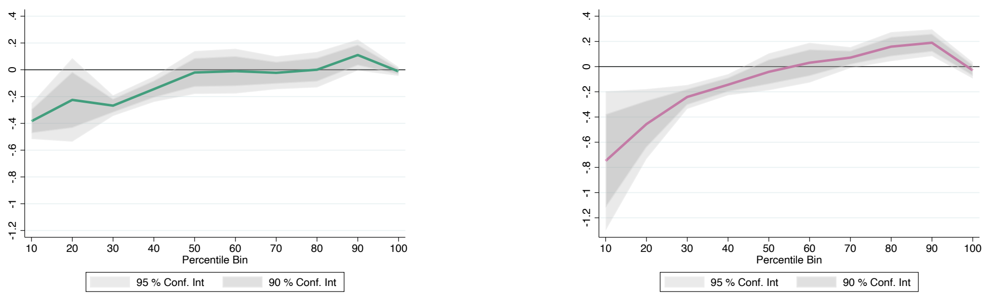
significant one and two years after the shock. This suggests that the new investment opportunity creates a trade-off for firms with low liquidity: to take the investment opportunity they need to reduce their working capital, leading to a potential decrease in labor demand. Firms with high liquidity do not face such trade-off and can expand in 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 7. Figure 8 shows the effect on wage growth on impact. Panel 8a shows the effect for firms with high liquidity, while panel 8b for firms with low liquidity. As expected, the negative effect on the bottom half of the distribution is more pronounced for firms with low liquidity. We interpret this result as evidence of the trade-off between increasing the capital stock and 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 that are substitutes for capital. As a result we can observe wages of some workers going down, and labor demand only expanding for some firms. The magnitude of the effect is significant. In firms with high liquidity, wages in the bottom of the distribution decrease 5.3% to a one standard deviation shock, whereas in low-liquidity firms wages fall by 10%. This means that low-income workers in firms with low liquidity disproportionately lose following a positive credit supply shock compared with the average worker or with the equivalent worker in a high-liquidity firm.

Figure 8: On impact heterogeneous response to a positive credit supply shock on 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 to wages in income bin using equation 7 for $h = 0$ in high liquidity firms, and Panel **(b)** for low liquidity firms. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time level.

In this section, we documented three outcomes following a positive idiosyncratic credit supply shock. First, we find that firms increase investment but the effect on employment and wages is small and insignificant. Second, we show that wages in the bottom half of the distribution decline. We interpret this result as evidence of substitutability between capital and workers with low skills. Third, we provide evidence for one potential mechanism that explains why given an expansion of credit, we observe an increase in the capital stock and a fall in low income wages. We find evidence that internal financial constraints of the firm matter for how firms respond to a positive credit supply shock. Firms that have high liquid asset holdings are more responsive to the shock and expand in scale. Firms with low liquid asset holdings reduce their working capital as a response to a positive credit supply shock and if something, contract 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 that is 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[25]. The role of the banks is the one of a pass-trough financial intermediary, where the presence of an intermediation

[25] The search block follows Shimer (2010)

premium generates a gap between the deposits rate and the borrowing rate. We define the credit supply shock as variations to the bank's intermediation premium. The labor market is divided in two separate markets, one for skilled workers and another for unskilled workers. 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. The household owns the firms, and the banks, and supplies labor.

In the model, time is discrete. The only source of uncertainty in the model is coming from changes to the intermediation premium -credit supply shock-. There is an aggregate state s_t vector 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 firm's environment to highlight how the interaction of the two types of labor with the working capital financed with the liquid asset, generate opposing forces on employment and wages. After setting the firm's 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, in the rest of the text we suppress the aggregate state s in 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 $n = \{z, u\}$. If employed the worker earns a wage w_n. If unemployed the individual does not receive 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 ρ_n. Unemployed individuals in t find jobs next period with probability $p(\theta)$, where θ_n is the market tightness in each labor market. The market tightness is the relationship between available vacancies and unemployment.[26] The household owns the bank and the firms, and receives dividends π^B and π^F correspondingly.

The recursive problem of the household is:

$$V_H(s, d^h, l_u, l_z) = \max_{c, d^h} U(c, l_u, l_z) + \beta \mathbb{E} V_H(s', d'^h, l'_u, l'_z)$$

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

subject to

$$c + d^h = w_u l_u + w_z l_z + \frac{1}{M(s'|s)} d'^h + \pi^F + \pi^B$$
$$l'_n = (1-\rho_n)\, l_n + p(\theta_n)\, u_n,\; n = \{u, z\}$$

The household receives utility for consumption and disutility for working in the following way:[27]

$$U(c, l_u, l_z) = \frac{c^{1-\sigma}}{1-\sigma} - \phi\frac{l_u^\nu}{\nu} - \phi\frac{l_z^\nu}{\nu},\; \nu > 1,\; \phi > 0$$

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

$$M(s'|s) = \beta E \frac{u_1(c', l'_u, l'_z)}{u_1(c, l_u, l_z)}$$

5.2 Banks

The banks are owed by the household and pay dividends π^B every period. Banks take deposits m from the firms. The banks pay an exogenous interest rate $r^m > 1$ to the firms for its 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 firms with a rate $R > 1$ for each unit of debt, that the banks takes as given.

The banks recursive problem is:

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

subject to

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

Where, $\theta(r^m - 1)\sum_{n=u,z} w_n l_n$ correspond to the early withdrawals 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 that exogenous changes to Z are the credit supply shock.[28] The intermediation cost follows follows an AR(1):

[27] 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).

[28] the role of the bank is similar to Jeenas (2019).

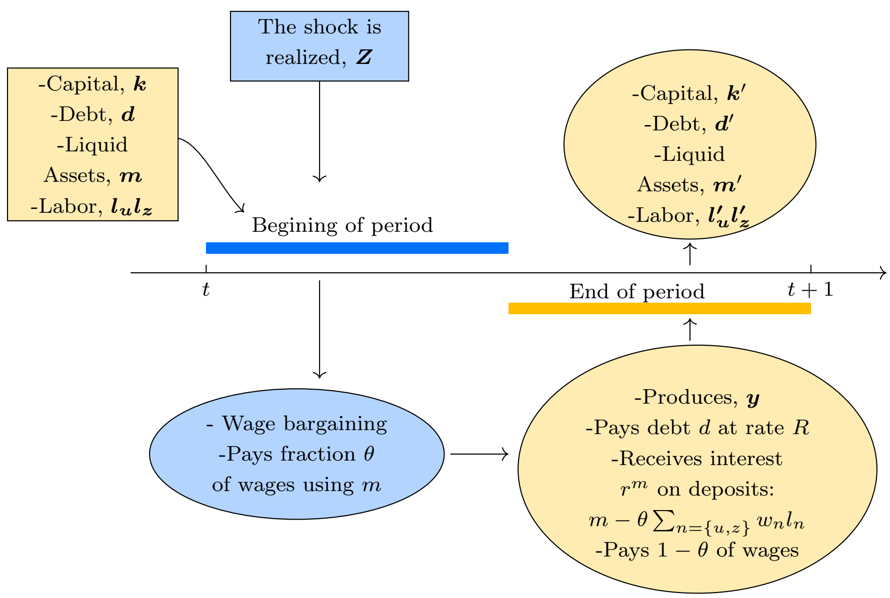
$$\log(Z_t) = \eta \log(Z_{t-1}) + \upsilon_t$$

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 $\tau(d')$. Where $\tau'(d') > 0$ and $\tau''(d') < 0$. We include this feature to keep the model tractable and simultaneously capture the risk of default in debt. We use as functional form for the debt elastic supply the following expression:

$$\tau(b') = \frac{1}{2}\big(\frac{b'}{k}\big)^2$$

5.3 Firms

The firms produce a final good using capital and two types of labor. The firm enters the period with capital k, debt d, liquid assets m as form of deposits in the banks, and two types of labor: skilled l_z and unskilled l_u. We divide the decisions within the period in two parts. Figure 5.3 illustrates the timing of the firm's decisions during the period.



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

At the end of the period, production $y = f(k, l_u, l_z)$ 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:

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

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 deposits rate. This implies that there should be at least enough deposits to finance the working capital:

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

When adjusting debt or capital, the firms pays 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 ζ_n. Every period, an exogenous fraction of workers ρ_n lose their jobs, while a fraction $q(\theta_n)$ of the firm vacancies are filled. Recall, that θ_n is the market tightness. After reorganizing some terms, the recursive problem of the firm is:

$$J(s, k, d, m, l_u, l_z, Z,) = \max_{l_n, k', b', m'} \pi^F + \mathbb{E}\Big(M(s'|s)J(s', k', d', m', l'_u, l'_z, Z')\Big)$$

subject to

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

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):[29]

$$f(k, l_u, l_z) = \Big(\mu(l_z)^{\eta_a} + (1-\mu)\Big(\mu_r k^{\eta_r} + (1-\mu_r)(l_u)^{\eta_r}\Big)^{\frac{\eta_a}{\eta_r}}\Big)^{\frac{1}{\eta_a}}$$

The first term represents non-routine 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, there are two key parameter to understand the effect of the credit supply shock on wages. One is the the substitution parameter between non-routine and routine activities η_a and the other is the substitution parameter between capital and low-skilled labor η_r

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

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

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

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

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 matching constant returns to scale 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 needs to be equal to the fraction of vacancies that are filled every period.

To clear each labor market the number of employed worker 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,

[29]There are multiple functional forms studied in the literature that can deliver capital-skill complementarities. See, for example, Stokey (1996), Krusell et al. (2000), Lafortune et al. (2019),Acemoglu and Autor (2011) ,Vom Lehn (2020)

and if it succeeds she receives the negotiated wage w_n. The bargained wage is the solution to the following problem:

$$\arg\max_{w_n} \tilde{V}(w_n)^{\mu_u} \tilde{J}(w_n(\lambda_{1f}))^{1-\mu_n}$$

Where $\mu_u \in [0,1]$ is the bargaining power of the workers. λ_{1f} is the Lagrange multiplier of the liquid assets constraint form the firms' optimization problem. It is important to notice that guarantee a solution, the firm always needs to have enough deposits to pay wages. $\tilde{V_n}(w_n)$ is the marginal benefit of 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, a state of 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_{zt}, $w_{ut}, R, M(s'|s)$- 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:

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

Recall that $M(s) = \beta\frac{u_1(c', l'_z, l'_u)}{u_1(c, l_z, l_u)}$ is the stochastic discount factor from the household problem. We interpret $\frac{1}{M(s)}$ 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:

$$(1 - \kappa_1(d', k)) = \mathbb{E}\big(M(s')R'\big)$$

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

$$\Big(1 + h_1(k', k)\Big) = E\Big(M(s')\big(f_1(k', l'_u, l'_z) + 1 - \delta + h_2(k'', k') + \kappa_2(d'', k')\big)\Big)$$

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 return on savings of the household and the return to liquid assets of the firm r^m. The firms' first order condition for the liquid asset is given by:

$$1 = \mathbb{E}M(s)\big(r^m + \lambda'_{f1}\big)$$

where λ_{f1} is the Lagrange multiplier for the money holdings constraint. Since r^m is fixed, when the constraint is binding, a reduction on the intermediation cost increases the shadow cost of liquid assets holdings λ_{f1}. This effect has an immediate implication for labor demand. Since the firms use liquid assets to finance the working capital, increasing debt demand is a force pushing labor demand down. After the Nash bargaining process, labor demand is given by the following expressions:

$$w_u = \Big(\mu_u MPL_u + \mu_u \zeta_u \theta_u + \frac{(1-\mu)\phi l_u^{(\nu-1)}}{u_1(c, l_z, l_u)}\Big) \times \frac{1}{1 + (r^m - 1 + \lambda_{f1})\theta}$$

$$w_z = \Big(\mu_z MPL_z + \mu_z \zeta_z \theta_z + \frac{(1-\mu)\phi l_z^{(\nu-1)}}{u_1(c, l_z, l_u)}\Big) \times \frac{1}{1 + (r^m - 1 + \lambda_{f1})\theta}$$

Where MPL_u and MPL_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.

There are two ways in which the presence of the two mechanisms - capital-low-skill substitutability- and a liquid asset to finance working capital - affect labor demand. First, when firms are unconstrained unconstrained firm, that is $\theta = 0$ changes on 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 inf 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-skill workers or capital with 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 think that a high liquidity firm in the data corresponds to a firm that does not have a 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 increases the tightening of the constraint, λ_{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, there are two opposing forces determining 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 ρ, and σ_Z. We find that $\rho = 0.37$ and $\sigma_Z = 0.19$ (See, Table 12 in the Appendix). There are two aspects worth highlighting: the shock is not very persistent and it is highly volatile.

One of the key aspects of 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 between 2008-2018. Since the rates are in pesos, we use the CPI to calculate annual inflation and use only real values.

We calibrate the deposits rate using the average fixed term deposits rate with annual maturity. Then, we set $r^m = 1.0261$. We set the discount factor to be equal to the inverse of the inter banking rate. This is, the rate for credit operations between banks. Since our model requires that $1/\beta$ to be the median rate in the market, we use the fifth percentile of the inter banking rate during the period 2008-2018, and we 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 value of steady state borrowing rate to math the average corporate credit borrowing rate. Table 13 in the Appendix reports summary statistics for these three rates.

For the firms parameters we use data from the firms financial reports, and some aggregate data at the national level. The key targeted moments in our model are the debt to capital ratio $\frac{d^*}{k^*}$ in steady state 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 κ to match the effect on debt and investment. We calibrate $\bar{d}$ and Z^* to satisfy the firm and banks debt Euler equations in steady state. Since the volatility of investment is determined in the model by the portfolio adjustment costs and $\frac{d^*}{k^*}$, we set ϕ 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 14). 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.

For the household parameters, since we do not observe hours or additional characteristics of the data, we follow the literature to set these parameters. The key parameter to 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 values of the elasticity of labor supply of these papers (1.66) are 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 correspondingly. 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 of labor supply parameter ψ to 1.8 following Neumeyer and Perri (2005).

For the search block parameters, we calibrate the cost of positing a vacancy ζ_n and the probability of destroying a match ρ_n in each market to match the average unemployment rate in Colombia during the sample period of 10.02% and the probability finding filling a vacancy in steady state of 0.7. We set the Nash bargaining parameters μ_u, and the matching function parameters ϕ_0, and ϕ_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 on debt, gross investment, employment, average wages, and wages by type of worker. Recall that 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 are always binding. Figure 9a shows the effect on debt and gross investment. The horizontal axis

Table 4: Calibration of the baseline economy

Parameter	**Symbol**	**Value**	**Source**
	Using micro data		
Persistence Shock	η	0.3698	AR(1) OLS estimation
Std. Dev Shock	σ_Z	0.1911	AR(1) OLS estimation
Steady-State debt holdings	$\bar{d}$	0.48	To match av. leverage
Portfolio adjustment costs	κ	0.9	Match estimates debt
Investment adjustment costs	ϕ	0.5	Match estimates debt
	Colombian aggregate data		
Discount factor	β	0.9241	Inverse p5 Inter bank rate
Int. cost in steady state	τ	0.1053	Diff. corp. and borrowing rate
Unemployment rate in steady state	$\bar{u}_n$	0.102	Unemployment rate
	Literature		
Depreciation	δ	0.0844	Standard Lit.
Capital weight	μ_r	0.39	Vom Lehn (2020)
Skilled weight	μ_a	0.38	Vom Lehn (2020)
Substitution capital-unskilled labor	η_r	0.4	Vom Lehn (2020)
Substitution skilled-routine	η_a	-2.22	Vom Lehn (2020)
Risk aversion	σ	2	Standard Lit.
Elasticity of labor supply	$\frac{1}{\nu-1}$	0.32	Leyva and Urrutia (2020)
Disutility of labor	ψ	1.8	Neumeyer and Perri (2005)
Nash Bargaining parameters	μ_u	0.5	Standard Lit.
Matching function	$\phi_0\phi_1$	0.5	Standard Lit.
Probability of filling a vacancy in steady state	$\bar{q}(\theta_n)$	0.7	Standard Lit.

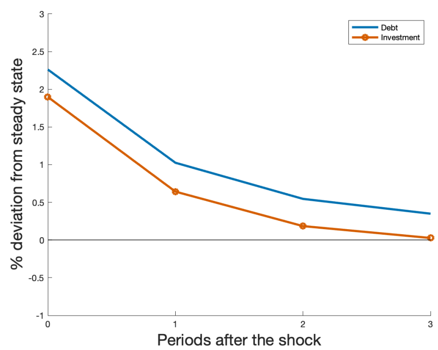
in this figure shows the periods after the shock. The vertical axis shows the percentage response to a one standard deviation shock. Recall that we calibrate the shock in the to have the same persistence the estimated shock in the the data. As we discussed before, we target the response on debt to be equal to the response of the estimates 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 9b shows the effect on the shadow value of holding money. With this figure, we want to highlight the trade-off that the firms are facing. In response to a positive credit supply shock, the opportunity cost of holding liquid assets increases, and the benefit of investment increases. Figure 19 in the Appendix, shows the effects on the borrowing interest rate, and the money holdings.

Figures 9c and 9d show the labor market results results. Figure 9c 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 wit 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 9d shows the effect on wages by type of worker. There, we observe how both mechanisms interact. On impact, similarly to figure 3 in the empirics, wages of low skilled workers decline, while wages of the high skilled workers increase. The negative effect is lasts for two periods for low income workers, while it becomes positive for high income workers. In other words, one period after the shock the effect of the working capital dominates the effect of the production function. As the liquid assets constraint becomes less binding, the effect of the 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 become more substitutes to capital, the negative effect on low-income workers disappears. Figure 20 in the Appendix shows the sensitivity analysis for the capital-low-skilled substitutability parameter. This parameter is of particular relevance for the effect three years after the shock.

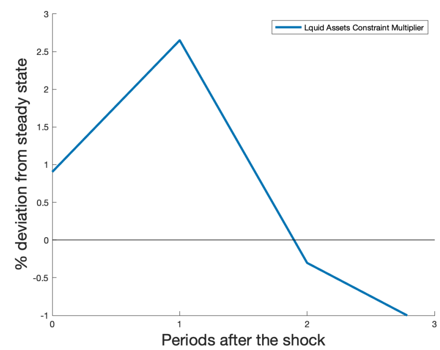
To understand the effect of a positive credit supply shock to unconstrained firms we simulate the model with no working capital (Figure 10). One point to emphasize is the magnitude of the change in debt and investment compared with the baseline model (See, Figure 21 in the Appendix). Similar to the data, our unconstrained firm is as responsive in terms of debt and investment compared with the constrained firm. Figure **??** shows the effects on average wages and employment. Contrary to what we observe with the baseline model both average wages decrease and employment increase. There are two reasons for this results. First, Figure 10b shows the effect on low-skilled and high-skilled wages. Similarly

Figure 9: Impulse Response Functions of a positive credit supply shock to investment, debt, wages and employment

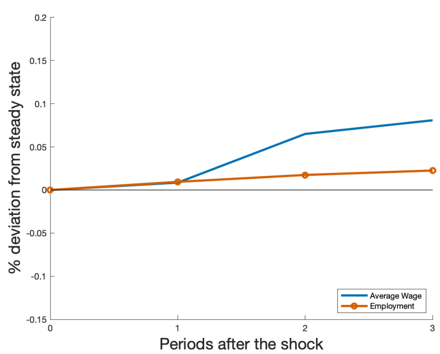
(a) Debt and Gross Investment



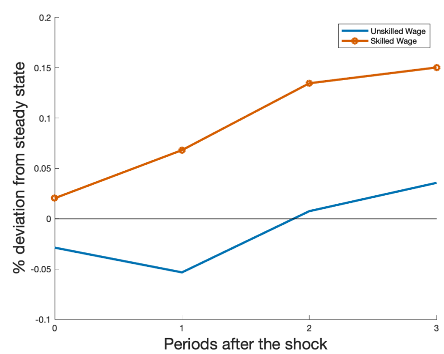
(b) Shadow Value of Liquid Assets



(c) Employment and Average Wages



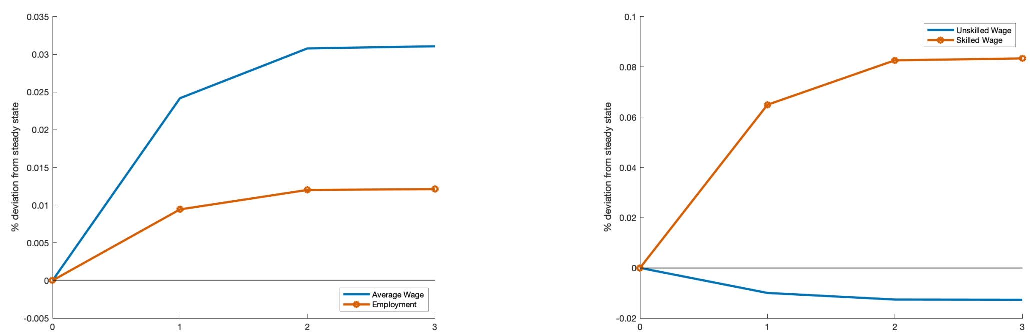
(d) Low and High wages



Note: Impulse response functions to the baseline model simulations.

Figure 10: Impulse Response Functions of 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 to the model without working capital.

to the data, the negative effect in low income workers is half of the effect of the constrained firm. Moreover, the effect on high-skilled wages is also larger. As a result, both employment and average wages increase more compared to the constrained firms results. In other words, since the firm does not face a trade-off between increasing capital or using liquid funds to pay for the working capital, we only observe the effect of the capital-low-skilled substitutability channel.

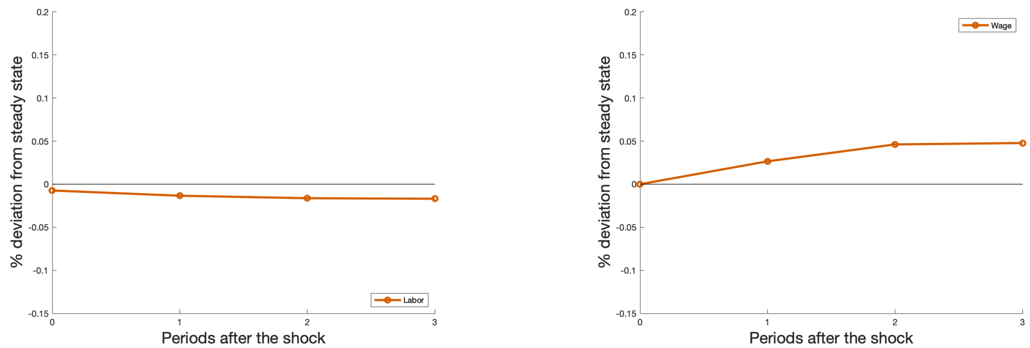
Finally, we explore the effects of a positive credit supply shock to a firm with one type of labor and working capital constraint (Figure 11). From this experiment it is important to emphasize that the effect on wages and employment is always negative, regardless of the elasticity of labor supply. Moving from the two extremes of the baseline model, no working capital and one type of labor, makes us depart further from the empirical results. Then, this suggests that the small changes on average wages and employments could potentially be explained by the interaction of both mechanisms. These two forces eliminate the effect on labor demand for high income workers. As a result, we only observe in the data changes at the bottom half of the distribution.

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. Instead, changes to credit supply have an effect on wage inequality. Also, from our model any policy that aims to expand corporate credit, and wants to affect wages needs to be accompanied by additional mechanisms to make liquidity constraints less binding. In this section we study how permanent changes in the intermediation premium, $\bar{\tau}$, change the response of employ-

Figure 11: Impulse Response Functions to a positive credit supply shock to wages and employment for firms with one type of labor

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



Note: Impulse response functions to the model with one type of labor

ment and wages to a credit supply shock. Studying changes to the intermediation premium is of particular interest in terms of policy because it is equivalent as to say "what would happen if we make banks more efficient".

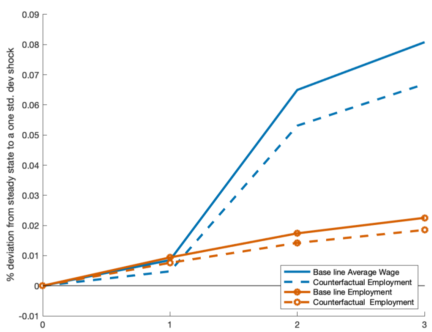
Our experiment consists in reducing $\bar{\tau}$ by 20%. A reduction of 20% in $t\bar{a}u$ is equivalent to reducing the borrowing rate in steady state from 8% to 7%. Figure 12 compares the impulse response functions of the base line model with the impulse response function of the counterfactual. Panel 12a compares the effect on average wage and employment, panel 12b shows the effect on skilled and unskilled wages. The result shows that when the intermediation premium is permanently smaller, low-skilled do not decrease as much as they do in the baseline model. For 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 than wages in 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 has a positive effect in reducing 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, and this translates in lower average wage, but also lower employment.

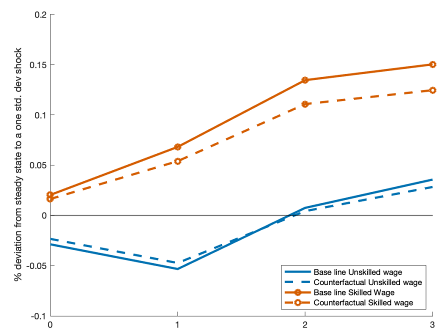
The mechanism works as follows. By improving ability of the bank to turn deposits into firm debt, the debt supply becomes less responsive to an equivalent shock (See, Figure 23a in the Appendix). Thus, in response to a positive credit supply shock, debt increase is 4 percentage points lower compared to the baseline model. This translates in a lower

Figure 12: Comparing the Impulse Response Functions o 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.

increase to the capital stock: the investment opportunity is not as large (See, Figure 23b in the Appendix). 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 23c and 23d in the Appendix). 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 the capital stock, the long-term effect hurts high-skilled workers, employment and average wages. In this sense, when we reduce the intermediation cost, and make banks more efficient the liquidity constraint becomes less relevant in the long run.

6 Conclusions

In this paper we ask how access ti corporate credit supply affect employment and wages outside financial-crisis episodes. To answer this question we create a unique data set from Colombia linking Banks-Firms-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 after the first two years of 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 firms with low liquidity 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 a "pass-through" 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 and there are 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 on debt and gross investment remains positive. In terms of the labor market, demand for high income workers increases, and demand decreases for 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 permanently down in reaction 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 deposits and borrowing rate. This experiment is equivalent to making banks more efficient in their pass-through function. With this experiment, we can conclude that if a policy maker 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 in terms of policy 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 has limited ability to produce 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 *Superintendencia Financiera*, which is 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, mortgages, consumption, and micro-credit. We use data only for commercial credits issued between January 2004 and December 2018 to firms that use as firm identifier a *NIT*. We organize the data in three steps. First, we clean the original reports to remove outliers, or transactions with incomplete information. Then, using these data we aggregate it at the firm and bank level, and then we use information on the last quarter of the year to estimate the annual credit shock using all transactions from the 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 where the lending institution is missing. After this, we recover each credit operation history and we keep credits 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 credit is complete if the first observation corresponds to the initial date, and the last observation corresponds to final credit date. With the incomplete credits, we consider that there might be a problem in some reports, and then we use a fuzzy merge algorithm to recover the missing dates. If after the fuzzy merge, we can have the entire history we keep the transaction, if not we drop it. If after identifying the history of a credit, there are two operations with identical credit identifier but different capital stocks and interest rates, we consider them as unique credits, and we 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 8 (typo). We drop credits if the interest rate is higher than the maximum legal interest rate of the period (33.51% 2017-1), and credits where number of default days is greater than maturity. We drop credits below $10000 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. We assume it is a typo. The reason is that these credits are on average of $200000 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 per transaction.

We use this data as input to estimate the credit shock and to compute bank and firm-level financial data[30].

After removing outliers and typos as we describe above, we aggregate the data at the firm-level and at the bank level separately. At this point, we do not consider the history of each credit, but 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 create the number of relationships per firm we go back to the original data and keep the initial, and the

[30]"Credit_Full_Comm_Quart.dta

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 that are registered as Banks.

We use information on the banks financial reports to define our banking sample. We keep banks that have 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 the financial report on December to compute the banks' size and their 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 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 cross-walk methodology between financial reports. First, we keep for each month and year the groups and classes, that is the broader classification in the financial report, and store the names of the accounts per 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 say that there is a different accounting methodology if the difference in description between two years is greater than 12%. We find that the variables description changed in 2015. Between 2014 and 2015, 81% of the descriptions are different. After identifying the differences, we manually look for the variables of interest in each accounting methodology.

Table 5: Summary Statistics Banks

	Mean	Std. Dev	P. 95	P. 5	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 Banks Financial Reports from Super Intendencia Financiera de Colombia.

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 that have less than five relationships. Only one bank in our sample had this issue, BWWB. Which is a small bank that entered the market in 2012. Then we use Amiti and Weinstein (2018) to estimate the credit supply shocks per year. After this, we compute the credit supply shock as weighted average of the banking portfolio per firm.

Table 6: Summary Statistics Banking Shock

	Mean	Std. Dev	P. 95	P. 5	N
Banking Shock$_{ft}$	0.05	0.13	0.27	-0.12	57168

Note: Summary Statistics of the credit supply shock

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. During this period we identify two different accounting methodologies: 2001-2010, Colombian old PUC accounts, 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 a year.

To define an accounting methodology, and to map variables between the 2000 methodology and the 2010 methodology, we proceed in two steps. First, we list all the possible names, second we merge identical names using a fuzzy merge algorithm. In the following two subsections we explain in detail how we proceed.

A.4.1 Variable Names

All firms submit an annual report from a format that has four ways of classifying information. The broader category is called *formato*, where they select the type of report. For example, the balance sheet corresponds to one of this broad categories, as well as the Income statement, and the general appendices in a regular financial report. Inside each of this forms, firms are asked to fill in particular information. Each observation is going to correspond to a numbered category, raw 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 follows *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 and 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 Forms Cross-Walk

To be able to compare information between methodologies we first create a cross-walk of the general forms (*Formatos*) using a fuzzy-merge algorithm. For each available form in 2007's methodology we compare merge names with the 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 4 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. By 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 methodology, the code in 2007, and all names.

We use this methodology to the cross walk of all forms but the balance sheet. Given that the balance sheet accounts are divided between Classes, Groups, Accounts and Subaccounts, and these ones are simultaneously divided in current and long-term accounts. We create a cross walk merging the codes. With these two procedures we end up with 1925 variables.

Table 7: Cross-Walk General Forms (*Formatos*)

Form Name 07	Form Name 2000	Form Number 07	Form Number 00
caratula		1	.
Anexo_1: ingresos de operacion	Anexo 01 ingresos de operacion	100	4000
Anexo_2: costo de ventas y de prestacion de servicios	Anexo 02 costo de ventas y de prestacion de servicios	200	5000
Anexo_3: costos indirectos y gastos operacionales de administracion y de ventas	Anexo 03 costos indirect. y gastos operacional. de admon 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: metodo de participacion patrimonial	Anexo 07c metodo de participacion 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 - submenu	Anexo 10a obligaciones financieras y proveedores	1001	13100
Anexo_11: movimiento de reservas y revalorizacion del patrimonio	Anexo 11 movimiento de reservas y de la revalorizacion del patrim	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 poseidas	Anexo 12b clases de inversionistas de acciones en circulacion	1201	15200
Anexo_12b: valor intrinseco	Anexo 12c valor intrinseco	1202	15300
Anexo_14: pensiones de jubilacion	Anexo 14 pensiones de jubilacion	1400	17000
Anexo_15: informacion general	Anexo 15a informacion 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 exteriory 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 administracion directa	Anexo 19 inventario de semovientes en administraciuon 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

A.4.3 Variables of Interest

This section describes the variables that we keep in the final data base, the general form of origin, and how we modify them. We divide our variables of interest in four categories: General Information, Balance Sheet, Liquidity constraints, International Exposure, and Labor. After dividing all of the information in these five categories, we keep firms that have all assets as positive values, and firms for which the basic accounting equation holds. Here we want to make sure we don't have substantial typos. Second, we verify that the report on capital -fixed assets- is always positive and that it does not contain 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 make sure that we don't have negative values on capital. If we do, we replace the observation to missing, and then if the previous and the following year are not missing, we impute the value as the average. Third, we drop firms if sales and operational costs are negative. Third, we drop firms that report a number of workers larger than 10% of the working age population in Colombia in 2010[31] or if the total wage bill is negative. Fourth, we use sectors and cities from the public report. The reason to this is that the firms original reports contain more typos 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, 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, and a gap between years of at most one. For those firms in which we have a one year gap we impute the values as the average between the previous and following year. We restrict this imputation to maximum one year per firm. After the imputation we drop the firms at the top 1% and bottom 1% of assets.

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

A.5 Cross-walk firms PILA-Super Sociedades

PILA uses workers and firms identifiers, *personabasicaid* and *id* respectively, that are exclusive for this database. For 2010 the database provides a crosswalk between the workers identifiers, that is, a unique pair *cédulas-personabasicaid*, but does not provide such for the firms. Therefore, our task consists on creating a crosswalk between 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 crosswalk 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* can 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 that provides accounting services, and can be registered as the accountant of firm

[31] 38693000 from DANE

Y who is of firm's X client. If this happens, this worker would be the accountant of firm Y in Super Sociedades and a worker of firm X in PILA.

In this sense, 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 directives act as legal representatives, and that this firms are large enough to have at least the main accountant in their payroll. Using this assumption, we first restrict our sample to *cédulas* in PILA where the crosswalk between *personabasicaid* -*cédulas* is correct. That is, to pairs where *personabasicaid*, and *cédulas* are actually unique. Second, we create a link between *NIT*-*cédulas*-*personabasicaid* 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, that are not reported as independent workers. This step gives us a set of possible matches. That is for every firm in Super Sociedades we create a set of possible firms in PILA. Third, we follow an iterative process where we eliminate possible *NIT* and *id* out of the information set once we can conclude a pair *NIT*-*id* starting with a stronger criteria. The next three sections describe in detail each of the previous steps.

Step 1: Cleaning Typos

Using the original crosswalk between *personabasicaid*-*cédulas*[32], we remove typos, non-numeric characters and *cédulas* with less than 8 digits[33]. We store this data as "cedulas_unicas.dta". Following a similar procedure, we use the original workers' information in Super Sociedades[34] and create pair *NIT*-*cédula*. We remove typos, non-numeric characters and *cédulas* with less than 8 digits. Also, we assume the NITs are free of the same typos (see other Data Appendix Super Sociedades). Here we restrict our sample to the first three legal representatives and the main accountant. We drop information about board members, auditor, and other legal representatives and accountants. We store this data as "cedulas_SS_all-cedulas_unicas".

Step 2: Generating link *NIT*-*cedula*-*personabasicaid*

In this step we are going to create two files. On the one hand, we are going to have a triplet *NIT*-*cedula*-personabasicaid 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 35364 firms. Out of those, 23760 have more than two years of data, and 19691 four or more. For the purpose of our estimations, we consider our universe to be the sample with four or more years of data.

[32] file name: personabasicaid_all.dta

[33] Before 2004, the sequence of the identification number had 8 digits and starting in 2004 it changed to 10 digits. See: registraduria.gov.co

[34] SuperSociedades_Formato1.dta

On the other hand, we create an equivalent file but using PILA, here we generate a triplet *id-cedula*-personabasicaid. To generate this triplet we use "cedulas_unicas.dta", and merge them with each December in PILA between 2010-2015. We only use December because Super Sociedades has information about the annual financial reports, and these reports are presented on December 31st each year. We also restrict our sample to non-independent workers, wages above minimum wage and on the 0.01% of the distribution[35], more than 15 days worked per month, workers with double report on 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 process of elimination 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 both data bases using a one to one condition, and only those pairs that matched. Then, we verify that both *NIT* and *id* are unique, and drop 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 24694 *NIT-id* pairs, this number corresponds to 69.8% of the total firms. Out of those, we recover 17929 firms that have more than 2 years of data, and 15202 firms with four or more years of data. These correspond to 75.5%, and 77.2% respectively

We start this process with strongest criteria to weakest, as follows:

1. **Unique-Unique**: We keep workers that only worked in one firm during the entire period (2010-2015) in Super Sociedades and that only worked in one firm during the entire period in PILA. We merge by cedulas. Using this criterion we obtain 14330 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 cedulas and year. Using this criterion we obtain 2384 firms.
3. **Unique group by year -Unique group by year**: An individual could have had more than one job in either data base per year, but the group of people working together is unique in both Super Sociedades and PILA. We create a new identifier, new_id, that sorts *cedulas* of each group, and merge by new_id and year. Using this criterion we obtain 2038 firms.
4. **Max mode by year - Max mode by year**: An individual could have had more than one job in either data base per year, but there is one firm in which the worker worked more years (the mode). The number of years must coincide in both data bases. 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 cedula mode. Using this criterion we obtain 1842 firms.
5. **Unique *cédula*, city, year - Unique *cédula*,city, year**: An individual could have had more than one job in either data base per year, but the triplet cedula-year-city is unique in

[35] We make this last restriction because we consider that wages above this number could be a typo

Super Sociedades and PILA. We merge by the triplet. Using this criterion we obtain 1564 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 is unique in Super Sociedades and in PILA. We merge by the triplet group of workers-year-city. Using this criterion we obtain 5 firms.

7. **Unique *cédula*, region, year - Unique *cédula*, region, year**: Same as criterion 5 but using region 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 region second element of the triplet. Using this criterion we obtain 2 firms.

9. **Repeat 1-4**: After the first elimination process, we repeat steps 1-4 iteratively until we do not have more matches. Let us use an example to explain why we repeat these steps. Suppose that you have one *cédula* associated with two *NITs* in Super Sociedades, and that same *cédula* associated with two *ids* in PILA. You eliminate one *NIT* with criterion 2, and one *id* with criterion 3. If we repeat criterion 1 we can merge the remaining pair. Using this criterion we obtain 1104 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 cedulas and conclude that a NIT corresponds to an id. Here, we only drop if *NIT* is not unique, but we don't drop if *id* is not unique. 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 criterion 9, we repeat criterion 1 iteratively. At this point we do not have enough 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 id, merge by the id and year and conclude that a NIT corresponds to an id. Here, we only drop if *NIT* is not unique, but we don't drop if *id* is not unique. 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 3 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 data base per year, but there is one firm in which the worker worked more years (the mode). The number of years must coincide in both data bases. Here, we only drop if *NIT* is not unique, but we don't drop if *id* is not unique. 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 2 firms.

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

17. **Repeat 1**: Using the same argument as criterion 9, we repeat criterion 1 iteratively. At this point we do not have enough information to repeat criteria 2-4. Using this criterion we obtain 149 firms.

A.6 PILA: Employers-Employee panel

To construct the employers-employee panel we use data from the firms monthly social security payments reports between January 2008 to December 2008, and data from the cross-walk 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[36] below half of the minimum daily wage. In Colombia, in contrast with the U.S, 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 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 region and city of the worker, the region and city of where the firm is registered, 4 digits ISIC codes and aggregate sectors, a dummy and variable whether the worker was in maternity leave. Moreover, using information about tax brackets in Colombia we construct net wages and total labor per worker[37]. Finally we convert all values to real dollars of December 2018. To do this, we first deflate the variables using CPI to remove Colombia's inflation, and then we use the average exchange rate of December 2018 -3208.263 COP to USD-[38]. The reason why we do it this way is to avoid

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

[37]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 1090 UVT, 19% if annual wage between 1090 and 1700 UVTs, 28% if annual wage is between 1700 and 4100 UVTs, and 33% if annual wage is greater than 4100 UVTs. The exchange rate between COP and UVTs is $27318.47 COP, approximately 8.5 USD in december 2018. There are some additional taxes and labor costs that 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 pays an additional tax of 10% before 2010 and of 208 after that date (*parafiscales*). We use these measures as robustness tests.

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

including exchange rate fluctuations in the analysis or price adjustments in the US. [39]

On 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 robustness we aggregate using data from all months and generates 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, there is still 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 it unemployment for simplicity. Second, we define employment status on the previous period. A worker can remain employed (EE), 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 one indicates if a worker started working on 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 working with a firm. It is important to notice that our measure of tenure is limited by the number of years of the data, 2008-2018. Finally we define if a worker was rehired by a firm. That is, the worker previously worked in a firm, was hired by another firm for at least one period or absent from the data. 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 between 18 and 60 years old in 2008. The reason for this restriction is because 18 is the minimum legal working age in Colombia and 60 is the legal retirement age for males[40]. However we want to observe the cohort that turned 60 in 2008 until the end of the sample. [41]

A.7 PILA: Firms Panel

We create a firms panel about the firm's 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. First create variables containing information about employment. We generate total employment of the firm as the total number of workers, number of entrants and of 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

[39] We store each year separately and call these files "PILA_monthly_hist_'y'.dta" where $y = \{2008, \dots, 2018\}$. The code that runs this step is named "PILA_monthly_hist_'y'.do" and it is stored in "PILA Organization"

[40] It is 58 for women

[41] We store two data bases, one for each version of aggregation. The version that uses annual averages is "PILA_workers_annual.dta", the version that only uses December is "PILA_workers_annual_dec.dta". We store both files in "PILA/Organization/Output"

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 on employment, wages and age, we generate for all variables its corresponding version in logs and their log changes. Finally we construct a block containing geographic and sectoral information of the firm. We construct a measure of the broad sector using information on the section letter of the ISIC revision 4 code on the first year that we observe the firm. We define 20 broad sectors following the international standard classification[42]. 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

C Appendix: Empirical Results

Table 8: Connected Set of Credit Supply Shock: All firms and banks are connected

Year	Allocation	Size	Fraction
2008	55484	55484	100%
2009	57145	57145	100%
2010	49486	49486	100%
2011	47091	47091	100%
2012	49965	49965	100%
2013	51506	51506	100%
2014	52567	52567	100%
2015	57021	57021	100%
2016	58925	58925	100%
2017	56797	56797	100%
2018	66399	66399	100%

C.1 Liquidity

Figure 14 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

[42]Agriculture, Mining, Manufacturing, Electricity, Water supply, Construction, Whole Sale, Transportation, Accommodation, Information, Financial, Real estate, Professional, Administration, Public, Education, Health, Arts, Other Services, and Extra.

Table 9: Summary Statistics growth rates

	Mean	**Std. Dev**	**P95**	**P5**	N
$\Delta \log(BankingDebt)$	-0.06	1.03	1.27	-1.47	17567
$\Delta \log(Capital)$	-0.03	0.74	0.65	-1.31	19451
$\Delta \log(Wage)$	0.02	0.25	0.34	-0.30	56875

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

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	18957	18920

Note: Robust Standard errors in parentheses clustered at firm and time level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimated effect on banking debt using equation 6 for $h = 0$. We measure banking debt from the financial reports as the ratio of banking debt to total debt.

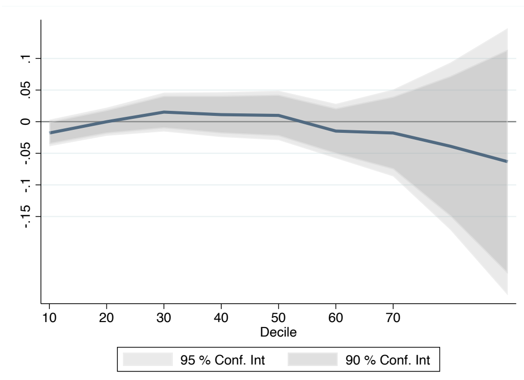
Table 11: On Impact effect of the credit supply shock on banking debt

	(1)	(2)
	$\Delta \log(BankingDebt)$	
Credit Shock	0.12**	0.14**
	(0.04)	(0.04)
Sales		-0.29***
		(0.04)
Locations		0.02
		(0.03)
Cash		0.13
		(0.10)
Leverage		0.13
		(0.09)
Firm FE	Yes	Yes
Time × Sector FE	Yes	Yes
N	21176	21101

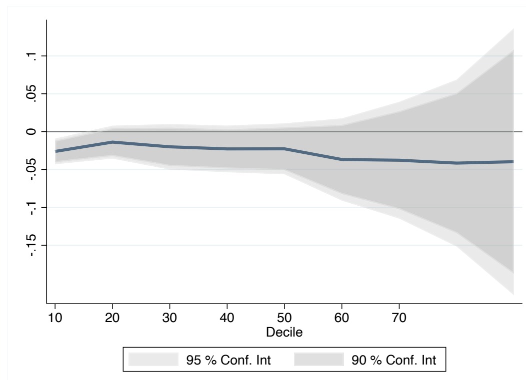
Note: Robust Standard errors in parentheses clustered at firm and time level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimated effect on banking debt using equation 6 for $h = 0$. We measure banking debt from the financial reports as the ratio of banking debt to total debt.

Figure 13: Effects on the wage distribution one and two years after a positive credit supply shock to incumbents and entrants

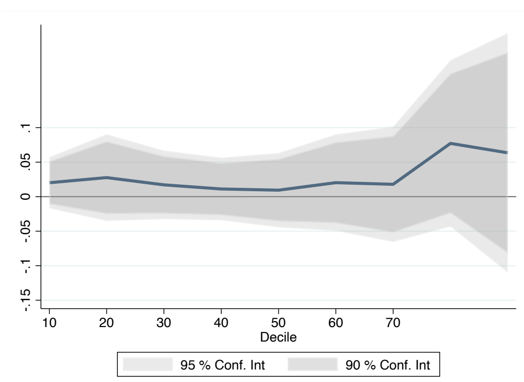
(a) Wages one year after to incumbents



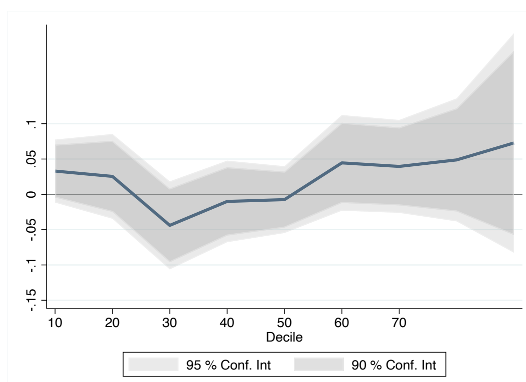
(b) Wages two years after to incumbents



(c) Wages one year after to entrants



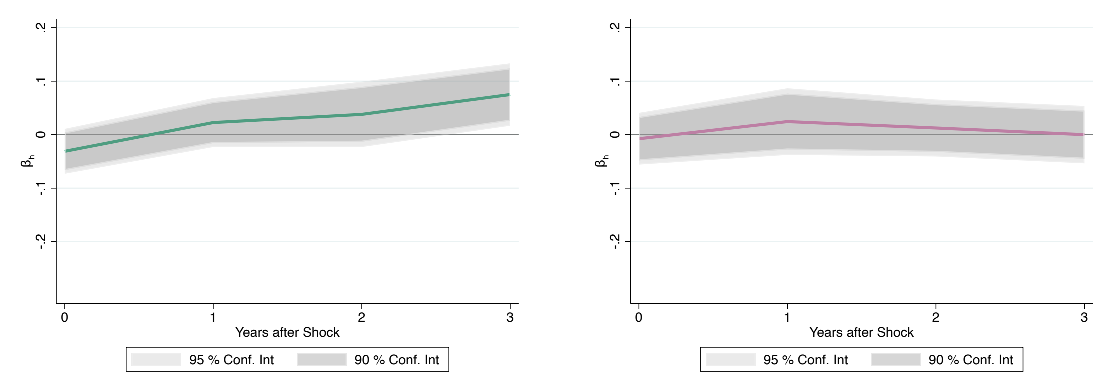
(d) Wages two years after to entrants



Note: Panel **(a)** shows the estimated effect on each income using equation 8 for $h = 0$. Panel **(b)** estimates it for $h = 1$ and Panel **(c)** for $h = 2$. Each regression for incumbents has 28183978 observations for $h = 0$, 1578695 for $h = 1$, and 1003026 for $h = 2$. Each regression for entrants has 1794380 observations for $h = 0$, 453462 for $h = 1$, and 292513 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the individual and time level.

Figure 14: Impulse response functions to average wages of high and low liquidity firms

(a) High liquidity firms **(b)** Low liquidity firms



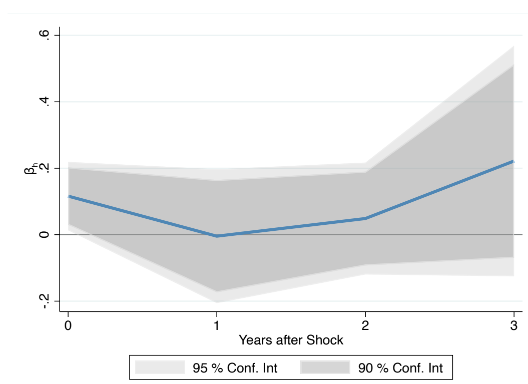
Note: Panels **(a)** shows the estimated effect on average wage using equation 6 for high-liquidity firms. Panels **(b)** and **(d)** shows the estimated effect on average wage using equation 6 for low-liquidity firms. A high liquidity firm is a firm with average cash and show term investment to assets ratio above the median. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time level.

the expansion of working capital two years after the shock for high liquidity firm in figure 7a. We do not find evidence of any effect for low liquidity firms.

C.2 Additional results

C.2.1 Large shocks

Figure 15: Large shocks increase employment on impact: Reconciling our results with Financial Crises Results in developed economies



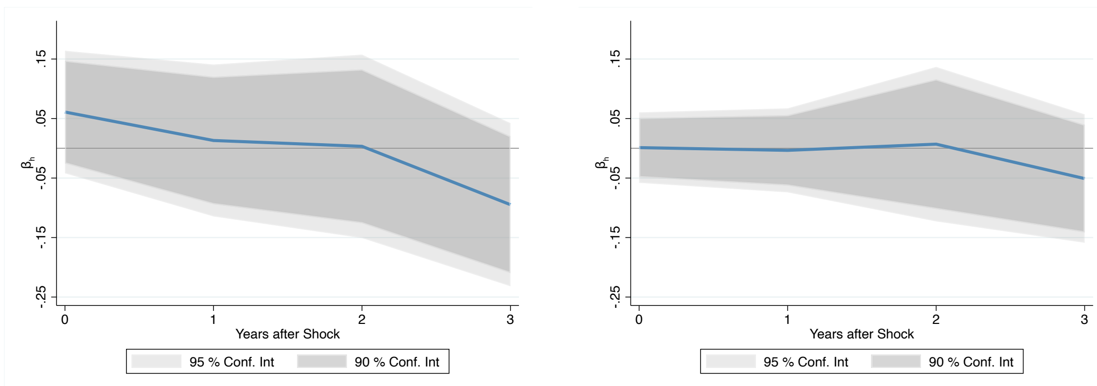
Note: Robust standard errors clustered at the firm and time level. All specifications include as controls lagged log sales, cash, log of number of locations, and demeaned leverage. Sample sizes: $h = 0$: 23125, $h = 1$: 16609, $h = 2$:12688, $h = 3$:10130.

C.2.2 Incumbents and entrants

We split our sample between incumbents and entrants. We estimate the effect on employment using equation 6 for each group. Figure 16 shows that there are 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 8. Figure 13 in the appendix 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 do not find different effects between these type of workers.

Figure 16: Impulse response functions to employment to incumbents and entrants

(a) Employment entrants **(b)** Employment incumbents



Note: Panels **(a)** shows the estimated effect on employment of entrants using equation 6 . Panels **(b)** and **(d)** shows the estimated effect on employment of incumbents using equation 6 for low-liquidity firms. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time level.

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 wages receive the the following wage:

$$\arg\max_{w_n} \tilde{V}(w_n)^{\mu_u} \tilde{J}(w_n)^{1-\mu_n}$$

Where $\mu_u \in [0,1]$ is the bargaining power of the workers. $\tilde{V_n}(w_n)$ is the marginal benefit of the household for having an ϵ extra workers employed at the current level of consumption and savings receiving wage w instead of $w(s)$, when ϵ tends to zero :

$$\tilde{V_n}(w_n) = u_1(c, l_z, l_u)(w - w(s)) + V_n(s, d^h, l_u, l_z)$$

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

$$\tilde{V_n}(s', d'^h, l'_u, l'_z) = u_1(c, l_z, l_u)w(s) + \beta(1 - \rho - p(\theta_n))V_n(s', d'^h, l'_u, l'_z)$$

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

$$\tilde{J_n}(w_n) = w(s) - w + J_n(s, k, d, m, l_z, l_u)$$

Where, by the firms first order conditions with respect to labor:

$$J_n(s, k, d, m, l_z, l_u) = mpl_n - w_n(1 + \theta(r^m - 1) + \lambda_{f1}) + \frac{\zeta_n(1 - \rho_n)}{q(\theta_n)}$$
$$\mathbb{E}M(s')J_n(s', k', d', m', l'_z, l'_u) = \frac{\zeta_n}{q(\theta_n)}$$

mpl_n is the marginal product of labor for each of the workers types:

$$mpl_u = \frac{(1 - \mu)\,(1 - \mu_r)\,f(k, l_u, l_z)^{1-\eta}}{l_u^{1-\eta_r}\left(\mu k^\eta + (1 - \mu)l_u^\eta\right)^{1-\frac{\eta}{\eta_r}}}$$
$$mpl_z = \Big(\frac{f(k, l_u, l_z)}{l_z}\Big)^{1-\eta}$$

The solution of the Nash bargaining problem is then:

$$\mu_n u_1(c, l_z, l_u)J_n(s, k, d, m, l_z, l_u) = (1 - \mu_n)V_n(s, d^h, l_z, l_u)$$

To solve for wages we plug in the solution of the Nash equilibrium problem in the household's first order conditions for labor to write them as function of $J_n(s, k, d, m, l_z, l_u)$ and $J_n(s', k', d', m', l'_z, l'_u)$. Then we use the firms' first order conditions of labor to solve for wages in terms of parameters, labor, and the market tightness:

$$w_u = \left(\mu_u mpl_u + \mu_u \zeta_u \theta_u + \frac{(1-\mu)\phi l_u^{(\nu-1)}}{u_1(c, l_z, l_u)}\right) \times \frac{1}{1 + (r^m - 1 + \lambda_{f1})\theta}$$

$$w_z = \left(\mu_z mpl_z + \mu_z \zeta_z \theta_z + \frac{(1-\mu)\phi l_z^{(\nu-1)}}{u_1(c, l_z, l_u)}\right) \times \frac{1}{1 + (r^m - 1 + \lambda_{f1})\theta}$$

D.2 Calibration

Table 12: Summary Statistics: Interest Rates Calibration

	(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 firm and time level.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Summary Statistics: Interest Rates 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 14: Summary Statistics: Firm Parameters

	Mean	Std. Dev	P95	P5	N
δ data	0.16	0.19			
δ PWT	0.04	0.00	0.04	0.04	10

D.3 Results

Figure 17: Impulse Response Functions of the credit supply shock

Figure 18: Banking Shock

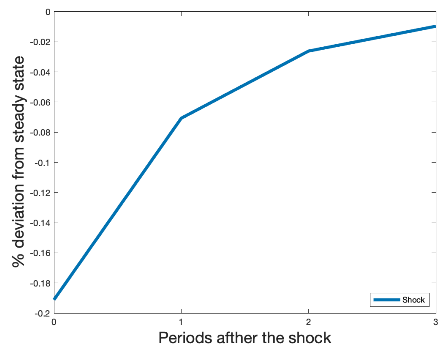
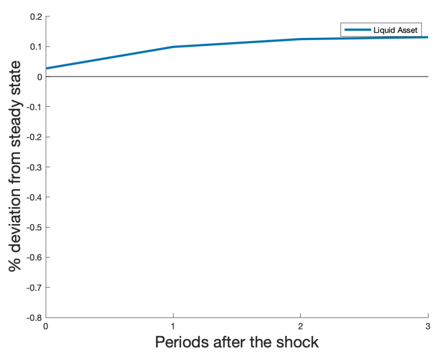
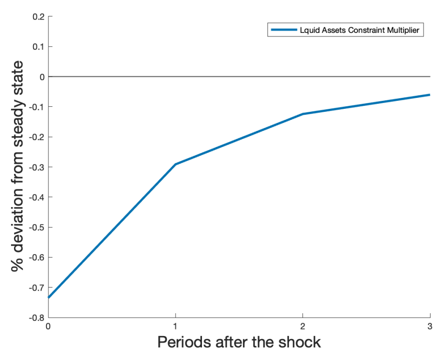


Figure 19: Impulse Response Functions to a positive credit supply shock to Liquid assets holdings and Borrowing Interest Rate

(a) Liquid Assets

(b) Borrowing Interest Rate

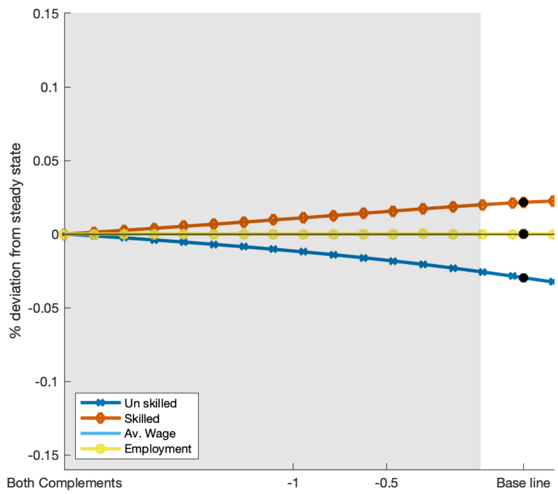




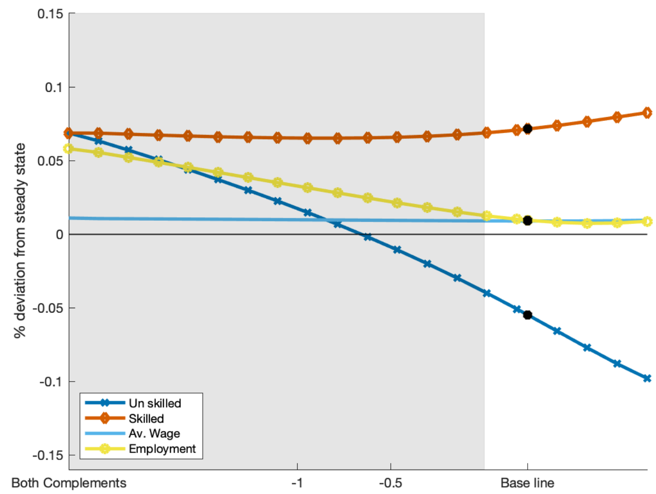
Note: Impulse response functions to the base line model simulations.

Figure 20: Sensitivity analysis of the labor market outcomes to the substitution parameter between capital and low-skilled workers η_r

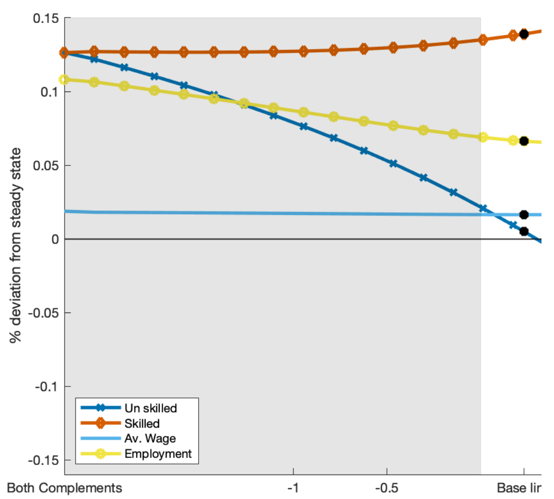
(a) h = 0



(b) h = 1



(c) h = 2



(d) h = 3

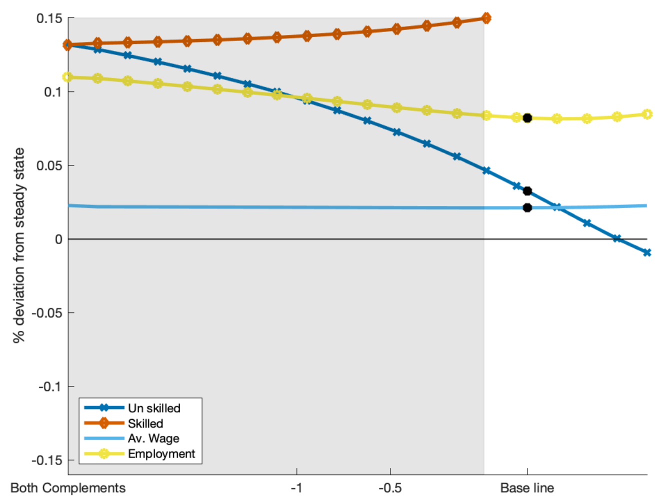
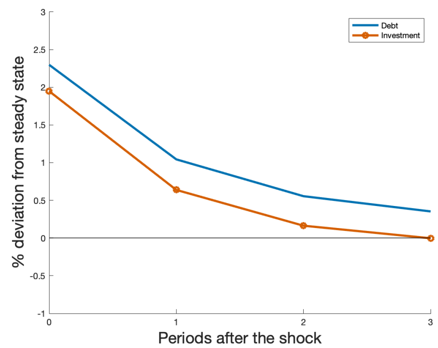


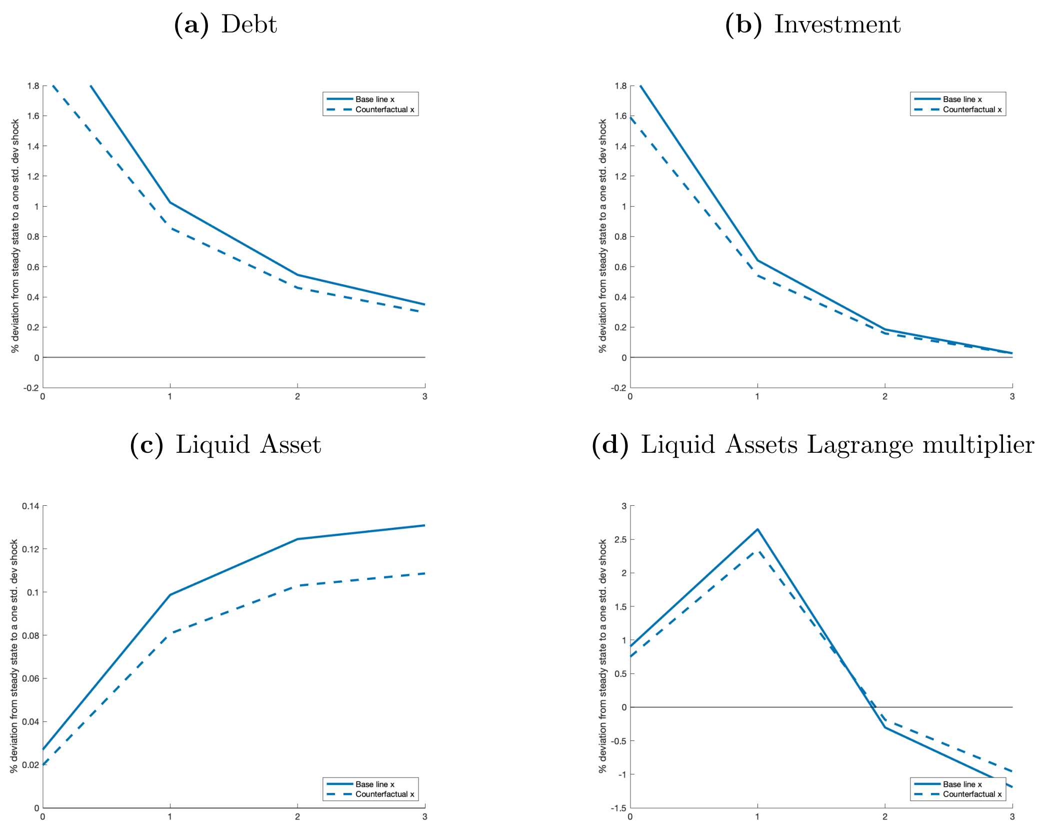
Figure 21: Impulse Response Functions of the credit supply shock to Debt and Capital of unconstrained firms

Figure 22: Banking Shock



D.4 Counterfactual

Figure 23: Comparing the Impulse Response Functions on debt, investment, and liquid asset to a positive credit supply shock for different levels of $\bar{\tau}$



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