Essays in International Macroeconomics

by

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Para la familia y los amigos.

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ABSTRACT

This dissertation studies three aspects of international macroeconomics and finance and their effects on employment, wages and investment.

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

the baseline model, we show a positive short-term impact on employment and wages and a negative long-term effect.

The second chapter, co-authored with John Leahy and Linda Tesar, is motivated by a set of cross-country observations on economic growth, structural transformation, and investment rates in a large sample of countries. We observe a hump-shaped relationship between a country's investment rate and its level of development, both within countries over time and across countries. Advanced economies reach their investment peak at a higher level of income and at an earlier point in time relative to emerging markets. We also observe the familiar patterns of structural change (a decline in the agricultural share and an increase in the services share, both relative to manufacturing). The pace of change observed in the 1930 to 1980 period in advanced economies is remarkably similar to that in emerging markets since 1960. Motivated by these facts, we develop a two-region model of the world economy that captures the dynamics of investment and structural change. The regions are isolated from each other up to the point of capital market liberalization in the early 1990s. At that point, capital flows from advanced economies to emerging markets and accelerates the process of structural change in emerging markets. Both regions gain from the liberalization of financial markets, but the majority of the gains accrue to the emerging economies. The overall magnitude of gains depends on the date of liberalization, the relative sizes of the two regions and the degree of asymmetry between the two regions at the point of liberalization. Finally, we consider the impact of a "second wave" of liberalization when China fully opens its economy to capital inflows.

The third chapter, studies the effects of financial crises on labor income inequality by exploiting cross-sectional variation at the county level in the U.S during the Great

Recession. Using declines in housing net worth to measure the intensity of the financial crisis the paper documents five empirical results. First, the 90-50 ratio of wages increases during and after the crisis in counties where it was more severe. Second, these changes are driven by increases in the 90th percentile between peak and trough, and by declines on the 50th percentile between peak and recovery. Third, there is no evidence suggesting that unemployment is driving the results. Fourth, these effects occur within industries. Fifth, changes in inequality are driven by differences in wages between High-Skill and Low-Skill occupations.

CHAPTER I

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

with Christian Posso

1.1 Introduction

The large rise in unemployment during the global financial crisis made clear the link between firms' access to credit and labor markets. An extensive literature has developed documenting these links and investigating the theoretical channels by which credit and labor markets interact (Mian and Sufi, 2014; Chodorow-Reich, 2014; Huber, 2018; Berton et al., 2018; Giroud and Mueller, 2017; Duygan-Bump et al., 2015; Baghai et al., 2018; Calvo et al., 2012). Financial crises, however, are extreme and rare events (Reinhart and Rogoff, 2008b) for banks, firms, and workers. In this paper, we shift the focus from crises to study how access to credit affects employment and wages when neither banks or firms are facing extraordinary conditions. To answer this question, it is necessary to track the links between banks, firms, and workers.

We create a novel administrative data set from Colombia between 2008 and 2018 that provides these links. We find that average employment and wages do not respond to an exogenous increase in credit supply. Instead, workers in the bottom of the distribution lose with these credit-supply expansions. Moreover, we find that the heterogeneous effect on workers is more pronounced in firms with low liquidity. We develop a model of financial frictions and labor markets to study the mechanisms and the aggregate effects.

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

We use administrative data of large firms in Colombia from three different sources.[1] First, we use financial reports from the Colombian government agency in charge of overseeing corporations, *Superintendencia de Sociedades*. Second, we use employer–employee data from the *PILA* system, which is equivalent to the Social Security

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

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.

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

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

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

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

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

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

To isolate the effect of each mechanism, we repeat our simulations turning off one channel at a time. We find that low-income wages slightly decline in the absence of liquidity constraints, while high-income wages increase relative to those offered by constrained firms. When the production structure only uses one type of labor, we find a small reduction in wages one period after the shock and a significant increase

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

later. Thus, the presence of both mechanisms is necessary to describe the observed in the data. Liquidity constraints and capital–low-skill substitutability force low-skilled wages permanently lower and induce more demand for high-skilled workers. When both mechanisms are in place together, the effects on average wages and employment are weakly positive.

Finally, we use our model to ask how reductions in the intermediation premium—the difference between the rate paid on bank deposits and the borrowing rate—influence firms' response to credit-supply shocks. We find that low-income workers do not lose as much as in the baseline model when the intermediation premium decreases by 20%. In particular, we find that one year after a positive credit-supply shock, low-skilled wages are 5% higher compared to our baseline model. In contrast, high-skilled wages are 8% lower. As a result, employment and average wages are lower compared to the original calibration. In this experiment, we reduce the importance of the banking shock as an investment opportunity. We allow credit-supply shocks to move around a permanent lower cost. When the economy as a whole faces lower borrowing interest rates firms do not respond as much to credit-supply expansions. Therefore, the trade-off between expanding capital and increasing labor demand is less apparent. The new change in access to capital is not large enough for low-liquidity firms to choose between capital and labor. Our results suggest that expanding credit has limited ability to produce changes in average wages and employment, but it can potentially increase labor-income inequality.

1.1.1 Related literature

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

Second, our study is related to the literature on financial shocks and firm dynamics (Amiti and Weinstein, 2018; Jiménez et al., 2019; Gilchrist et al., 2017; Kim, 2018). Methodologically, our paper closely follows Amiti and Weinstein (2018),[3] identifying credit-supply shocks through bank–firm relationships using bank and firm fixed effects. Our paper is related to the research that studies price-setting decisions and

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

margins of adjustment from credit-supply shocks (Gilchrist et al., 2017; Kim, 2018). It is similar to this literature in two ways. We study the effects of credit shocks and liquidity on the price of labor. We also highlight the importance of the liquidity channel. In this sense, our contributions to this literature are twofold. First, we bring a new data set in which we are able to link banks, firms, and workers. This data allows us to further understand the effects of a credit-supply shock beyond those at the aggregate level. Second, to our knowledge, ours is the first paper that studies how corporate credit-supply shocks affect wages from the firm perspective. We find that capital–skill substitutability and liquidity constraints are key to understanding our results. Our paper underscores the importance of credit shocks for firm choices not just during crises, but also during normal times.

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

The remainder of the paper proceeds as follows. Section 1.2 describes the data. Section 1.3 shows the results of the credit-shock estimation. Section 1.4 describes the empirical strategy and the main results of the paper. Section 1.5 describes the model and the simulations. Section 1.6 concludes.

1.2 Data

In this section, we explain the sources of the data and the linking process between three administrative-data sources. Our banking data comes from the Colombian government agency in charge of overseeing financial institutions, *Superintendencia Financiera*. Colombian banks and credit institutions are obligated to report the balance of all their credit operations every quarter (*Formato 341*). This information allows us to track the total amount of lending from a bank b to a firm f from the first period of the loan until its maturity. We restrict our data to credit issued between January 2008 and December 2018. We keep credit lines with maturity greater than 1 day and less than 90 years, with complete history,[4] with total initial debt above 10,000 COP (around 3 USD), and with interest rate below the legal maximum rate of the period (33.51% in 2017-1). In addition, we restrict our sample to banks with more than three years of data and to banks with more than five relationships. Then, to aggregate the data at the firm level, we keep the debt stock for each bank–firm in the fourth quarter. See data Appendix A.1.1 for more details about the data-organization process. Our final sample has 138,683 firms and 16 banks.[5] We also use banks' publicly available monthly financial statements from the *Superintendencia Financiera*. See Appendix A.1.1 for more details.

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

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

At the firm level, we use financial reports and their corresponding appendices from the *Superintendencia de Sociedades*, the government agency in charge of overseeing corporations. Firms with either annual sales or assets of more than 20,000 times the legal monthly minimum wage (about 4.11 million USD) are obligated to report.[6] We use the annual reports from 2008–2015[7] and restrict our sample to firms that report positive sales, assets, liabilities, and equity, verifying that in all reports the basic accounting identity holds. See, Appendix A.1.4 for details about the data-organization process.

A contribution of our paper is the ability to link banks' corporate credit reports with firms' financial statements and workers' employment histories. That is, we link credit reports—*Formato 341*—with financial reports—*Super-Sociedades*—and with social security payment reports—*PILA*. Colombia uses a unique official identifier for each corporation and for each individual. The corporations' unique identifier is called *NIT—número único de identificación tributaria*. This number identifies banks and firms in our data. We can think of the *NIT* as the equivalent to the United States' EIN—*employer identification number*. The individuals' unique identifier is called *cédula*, and it is comparable to the United States' SSN—*Social security number*. To link the credit reports and the financial statements we use the banks' and firms' *NIT*s. The link between the financial reports and the workers' employment history is more challenging. As we mentioned before, the financial reports identify firms using *NIT*s. The social security payment reports, however, use a different identification

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

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

system. This database does not use *NIT*s and *cédulas* to identify firms and workers. We developed a merging algorithm where we create a one-to-one mapping between the national firm identifiers *NIT* and the *PILA* identifiers. See Appendix A.1.5 for details about the merging algorithm.

After identifying the link between *NITs* and *PILA* firm identifiers, we construct the employer–employee data set. We use data from the firms' monthly social security payment reports—*PILA*—between 2008 and 2018, restricting the sample to the firms we identified. Each formal employer in Colombia reports every month the social security payments to each worker based on their basic monthly wage. We drop observations that have a daily wage below half of the minimum daily wage. We construct the daily wage as the monthly wage divided by the number of reported days.[8] We move from monthly to annual frequency using only information for December each year. With this method, we observe year-to-year changes that coincide with the date of the financial reports.[9] To address seasonality concerns, we verify our results by aggregating the data using information from all months. We generate monthly averages, following Alvarez et al. (2018). See Appendix A.1.6 for more details about the organization process. We deflate each variable using the December 2018 average monthly Colombian CPI and the December 2018 COP/USD exchange rate.

Our final sample contains 10,835 firms and 3,321,640 workers. Our sample corresponds to large financial firms in Colombia,[10] not only in terms of sales, but in number of employees and average wages. Table 1.1 shows that, on average, a firm in our sample has more than 100 employees, sales of almost 11 million USD per year, and

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

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

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

Table 1.1: Summary Statistics

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

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

a leverage to total assets of 38%. Our sample is comparable in terms of employment and leverage to firms in COMPUSTAT in the United States. In terms of wages, on average, our firms pay lower wages than U.S. firms, but higher wages compared to the Colombian market. The average wage in our sample is $542.96 dollars per month, about twice the average minimum wage of the sample period.[11]

1.3 Identifying Shocks to Credit Supply

To identify shocks to credit supply at the firm level, we closely follow (Amiti and Weinstein, 2018, hereafter AW). This framework, identifies credit-supply shocks as the firms' common change in borrowing from a particular bank. In other words, we measure the firm–bank pair variation in borrowing explained by changes in credit supply. This methodology is a generalization of a common identification strategy in the literature of financial shocks (Jiménez et al., 2019; Mian and Sufi, 2014; Iyer et al., 2014; Schnabl, 2012; Khwaja and Mian, 2008). The AW methodology differs from the rest of the literature in the sense that it does not take a stand on the nature of

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

the credit-supply shock. Instead, it relies on the structure of the banking system to identify shocks using firm and bank fixed effects. To be concrete, suppose a particular firm, f, borrows some quantity d_{fb} from a bank b. In each period t, debt can change either due to a shift in firm f's borrowing from all banks (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 is summarized in equation (1.1)

$$\Delta d_{fbt} = \alpha_{ft} + \beta_{bt} + \epsilon_{fbt} \tag{1.1}$$

AW show that expressing changes in debt of firm f from bank b as percentage changes and estimating equation (1.1) with weighted least squares (WLS) provides a consistent estimator of β_{bt}. Also, the estimation procedure allows for creation and termination of credit relationships,[12] and it is possible to aggregate at the firm level keeping a reasonable economic interpretation of the shocks.

To allow for the creation and destruction of bank–firm relationships and to give an economic interpretation, we renormalize equation (1.1) by adding an intercept c and leaving as omitted categories the first bank and the first firm:

$$\Delta d_{fbt} = c_t + \tilde{\alpha_{ft}} + \tilde{\beta_{bt}} + \epsilon_{fbt}, \tag{1.2}$$

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

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

fluctuations. We use as omitted category the median firm and bank shocks from equation (1.1) following Amiti and Weinstein (2018).

We estimate equation (1.2) using WLS. Then, we use the estimated bank fixed-effect coefficients and aggregate them at the firm level to define a credit-supply shock.[13] We use as weights the importance of each bank b in firm's f debt in period $t-1$:

$$\theta_{fbt} = \frac{d_{fbt-1}}{\sum_b d_{fbt-1}}. \tag{1.3}$$

We define a credit-supply shock as

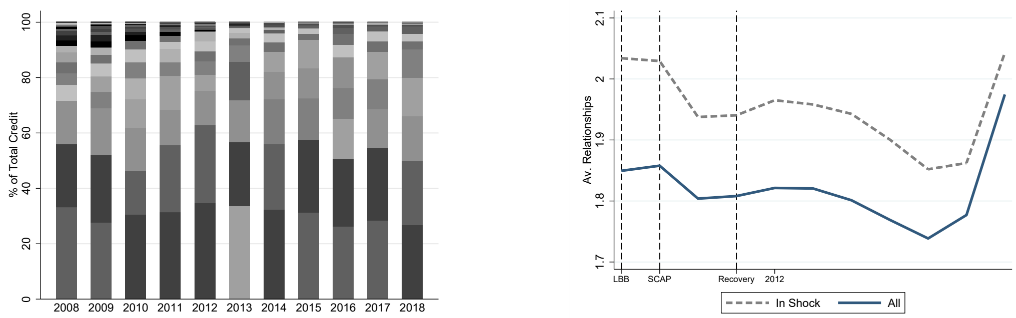
$$\textit{Supply Shock}_{ft} = \sum_b \theta_{fbt-1} \hat{\hat{\beta}}_{bt}. \tag{1.4}$$

We interpret a change in loan supply to firm f relative to the average change in credit supply as a credit-supply shock, idiosyncratic changes in the credit supply. This method of estimating credit-supply shocks has two particular features. First, it identifies idiosyncratic shocks. In this sense, it differs from the literature that studies the firm-level effects of aggregate credit-supply shocks (Chodorow-Reich, 2014; Huber, 2018). Second, it requires a particular structure of the banking system. Given that this method relies on fixed effects, we need sufficient overlap between banks and firms, a set of banks and firms that are connected to each other. If a bank lends to only one firm, it is not possible to identify if changes in debt are coming from the bank or from the firm. An equivalent situation arises if all firms borrow from all banks. We want to capture relative differences in credit supply. We also need granularity of banks. This

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

Figure 1.1: Identifying Assumptions of the Banking Shock

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



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

means that we need a large set of banks, in which the presence of all banks and firms is nonnegligible, but no one bank can be crucial to the existence of the market. We require granularity to argue that changes in one particular bank can have aggregate effects. If all banks have a negligible impact on the market, the failure of one bank does not affect the equilibrium outcomes. Figure 1.1 illustrates both of the conditions required for identification. Panel A shows that two of the banks—Bancolombia and Banco de Bogotá—control 40% of the credit portfolio. This situation guarantees the relevance of some of the banks in the market without allowing any one bank to be completely dominant. Similarly, Panel B shows that on average, firms have more than one banking relationship over time. We highlight that the credit reports' structure offers an ideal setting to estimate these idiosyncratic credit-supply shocks.

We estimate equation (1.2) from the credit data and validate our results with the banks' cross section using the banks' publicly available financial reports merged with our estimates of the credit-supply shocks. See Appendix A.1.2 for the data-organization process.[14]

[14] Table A.4 in the appendices shows that all firms and banks are connected.

We first verify that the $\hat{\hat{\beta}}_{bt}$ are positively correlated with the percentage change of commercial credit reported from the banks' balance sheets. We estimate $\hat{\hat{\beta}}_{bt}$ using Δd_{fbt} from the credit reports and expect our estimated $\hat{\hat{\beta}}_{bt}$ to be correlated with the percentage change in lending, Δd_{bt}, from the banks' balance sheets but different from one because the change in lending is an equilibrium object. The first column of Table 1.2 shows this result. We regress $\hat{\hat{\beta}}_{bt}$ on the percentage change of commercial credit and on time fixed effects using OLS. As expected, the coefficient is less than one and statistically significant at $p < .01$.

In addition, we expect $\hat{\hat{\beta}}_{bt}$ to be related to measures of bank health. Our shock captures the cross-sectional changes in credit supply relative to the median bank. That is, we expect healthier banks to experience positive credit-supply shocks compared to unhealthier banks. Even though our methodology does not take a stand on the interpretation or economic nature of the credit-supply shock, we can imagine situations that increase credit supply. Examples include bank marketing activities that increase the number of deposits and extra returns in investments other than

Table 1.2: The Credit-Supply Shock Is Correlated With Healthier Banks

	(1)	(2)	(3)	(4)
		$\hat{\beta}_{bt}$		
Δ 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.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

corporate credit. In this sense, we use as measures of banking-health dividend payments, checking and savings deposits as shares of deposits (CASA), and liabilities to capital as a measure of capital adequacy. We use dividend payments instead of market-to-book ratio[15] because most banks in our sample are not publicly traded. To address the limitation of our sample, we follow Khwaja and Mian (2008) and use the CASA ratio as a measure of liquidity. Banks with more checking and savings deposits have liquid funds that do not require high interest payments. As a final measure, we consider the capital adequacy of the bank measured as total liabilities divided by the bank's registered capital. We expect a negative correlation between our measure of capital adequacy and the credit-supply shock. Columns 2–4 of Table 1.2 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 (1.1) captures the year-by-year cross-sectional variation of borrowing coming from the banks. Thus, the common components of the business cycles are absorbed. When we normalize by the median shock per year, instead of an arbitrary bank, we measure change in credit coming from the bank that is different from the aggregate component. However, because we estimate the shock year by year, we might expect some anticipation of the shocks or some aggregate effects transmitted through the banks. In Table 1.3, we estimate an AR(1) model of the credit-supply shock, and add as control the cyclical

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

Table 1.3: 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 smoothing parameter $\lambda = 400$. Column 2 uses on impact GDP, Column 3 uses lagged GDP, and Column 4 uses forward GDP. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

component of GDP using an HP filter on impact, one period before and one period forward. These results suggest two important conclusions. First, the shocks have a small but statistically significant autoregressive component. That is, some bank characteristics that affect credit supply persist over time. Second, the credit-supply shock is not correlated with the business cycle. This is important because, as we said, our goal is to capture changes of credit supply that are different from aggregate components or financial crises.[16]

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

[16] Given some persistence of the shock, we verify our firm- and worker-level results using only the residuals of the estimates in Column 1 of Table 1.3. Our results are robust to this change. However, we prefer the original specification to maintain the economic interpretation of the estimated coefficients.

1.4 The Effect of Credit Shocks on Employment and Wages

1.4.1 Methodology

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

At the firm level, we estimate

$$\log Y_{ft+h} - \log Y_{ft-1} = \beta_{0h} + \beta_h \, \textit{Supply Shock}_{ft} + X_{ft-1}\Gamma_h + \alpha_{jth} + \alpha_{fh} + \epsilon_{fth}, \tag{1.5}$$

where Y_{ft+h} is a firm-level outcome of interest (investment, employment, or 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, β_h, measures the cumulative change in Y_{ft+h} to a one-unit increase in the credit supply relative to the median h years after the shock, a Jordá projection (Jordà, 2005). Because we only have firm-level controls until 2015, we study the effect up to three years after the shock given the number of years in our data, $h = \{0, 1, 2, 3\}$. We use our estimates of the credit-supply shock in equation (1.4) as our measure of the credit-supply shock.[17] Our controls include firm size in terms of sales and number of locations, liquid assets to total assets,[18] and demeaned leverage. Our controls are in line with Ottonello and Winberry (2020), Amiti and Weinstein (2018), and Gilchrist et al. (2017). We cluster the standard errors at the

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

firm and date levels and use this specification to study the aggregate effects and the firm-level heterogeneity.

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

$$\begin{aligned}(1.6)\quad \log(w_{ift+h}) - \log(w_{ift-1}) &= \beta_h\, \mathit{Supply\ Shock}_{ft} \\ &+ \beta_{hd}\, \mathit{Supply\ Shock}_{ft} \times \mathit{decile}_{it-1} + X_{ift-1}\Gamma_h + \alpha_{fth} + \alpha_{ih} + \epsilon_{ifth},\end{aligned}$$

where, decile_{it-1} is the workers' position in the wage distribution 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, $\beta_h + \beta_{ht}$, measures the cumulative change in w_{ift+h} after a one-unit increase in the credit-supply h years after the shock for each of the wage deciles. We use as additional controls the worker's age and age squared as to proxy experience. We cluster the standard errors at the firm and time levels.

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

$$(1.7)\qquad p\,(\log(w_{ift+h})) = \beta_0 + \beta_s\, \mathit{Supply\ Shock}_{ft} + X_{ift-1}\Gamma + \alpha_{fth} + \alpha_i + \epsilon_{ifth}.$$

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

1.4.2 How credit supply affects investment, employment, and wages

First, we establish a positive effect of the credit-supply shock on banking debt. We measure a firm's banking debt as the total debt from all domestic banks using data from the firms' financial reports. Figure 1.2a shows that the effect of a positive credit-supply shock on banking debt is significant on impact and goes to zero after that. Table A.6 in the appendices shows the effect without firm-level controls. We highlight two points. First, this fact offers proof of concept for our credit-supply shock. Recall that we use data from credit reports to estimate changes in credit availability. A positive change in banking debt from the balance-sheet perspective implies more credit availability results in an actual change in borrowing. Second, the effect is temporary, but large. A firm that receives a positive credit-supply shock of one standard deviation (0.13), increases its debt position with the banks by 2.34% (0.18×0.13). This effect is sizable compared to the average banking-debt growth rate, -6%.[19]

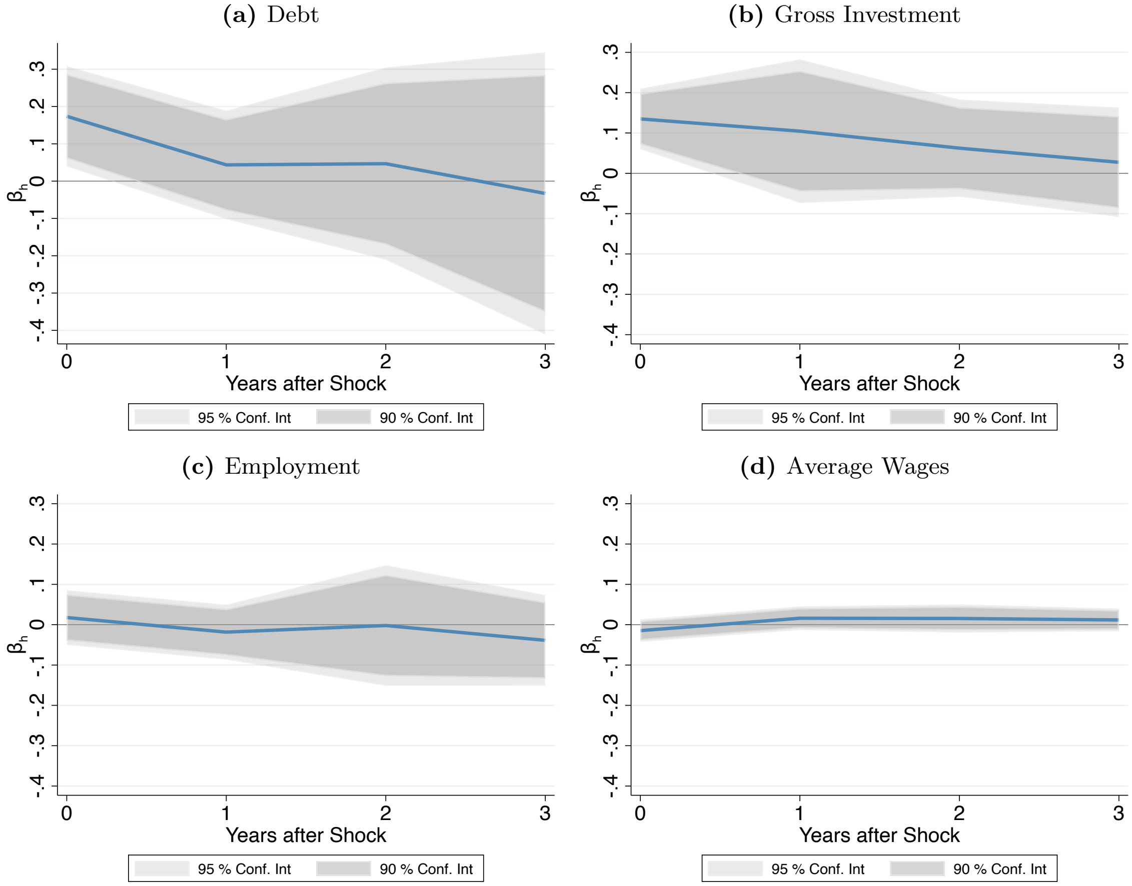
Figure 1.2b shows the effect on gross investment. We find that a positive credit-supply shock causes gross investment to increase on impact.[20] We interpret this as follows: When banks expand corporate credit, this translates into one period of borrowing. Firms use these new funds to finance investment projects to increase their capital stock. All of the new resources are used in the same period.[21] The size is again quite large. On average, the firms in our sample have decreased their capital stock 3%

[19]Table A.5 in the appendices summarizes the one-year growth rates of the main variables of interest.

[20]Measured as change in the physical capital.

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

Figure 1.2: Impulse Response Functions to a Positive Credit-Supply Shock



Note: Panel **(a)** shows the estimated effect of a positive credit-supply shock on banking debt using equation (1.5). We measure banking debt from the financial reports as total debt from domestic banks. Panel **(b)** shows the effect on capital stock. Panel **(c)** shows the estimated effect on employment using equation (1.5). We measure employment as the total number of workers. Panel **(d)** shows the effect on the average wage. We interpret the change in capital as gross investment. We report the 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

per year, and the effect of a one-standard-deviation shock is 1.8% (Tables A.5 and **??** in the appendices). The effect on debt is smaller than the effect on the capital stock. The average firm receiving a one-standard deviation credit-supply shock increases capital stock by 0.29 million USD and debt by 0.15 million USD. This implies that firm raise funds from other resources, like cash.

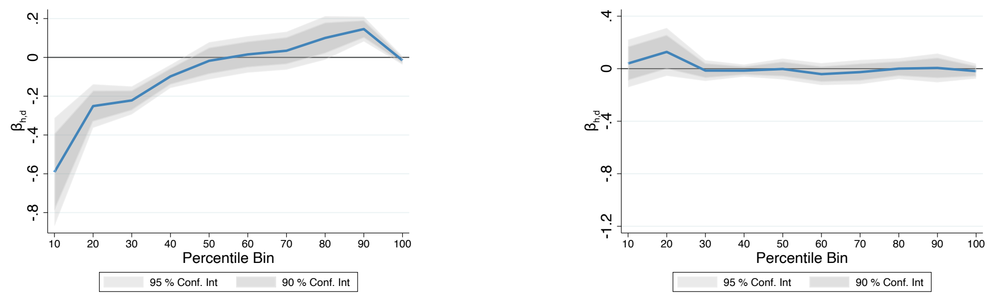
We now turn to the effects of the credit-supply shock on labor market outcomes. We do not find a significant effect on employment or average wages. Figures 1.2c and 1.2d show the impulse response functions for employment and wages, respectively. From the graphs, we can not only conclude that the effect is not statistically significant, but its magnitude is also small. This result is quite surprising compared with previous findings on employment changes during financial crises. In particular, Chodorow-Reich (2014) and Huber (2018) find that after the global financial crisis, employment declined for firms that had relationships with more affected banks. To reconcile our results with theirs findings, we repeat our estimates for employment only allowing for large shocks. We define a large shock as a credit-supply shock to a firm that is one standard deviation above or below the median shock in a particular year. Our goal with this exercise is to try to capture the closest scenario to a financial crisis, a period with a large volatility of credit supply. Figure A.3 in the appendices shows a positive and significant effect on employment on impact. This, highlights the importance of understanding the effects of credit supply on employment and wages outside financial-crisis episodes.

1.4.3 Uneven effect across types of workers

We exploit worker-level variation to estimate the impact of corporate credit-supply shocks on the distribution of workers or distribution of wages across workers. First, we study the effect on the growth rate of wages by decile, and then we study the level effect on the distribution of wages. To estimate the effect on wage growth, as described in equation (1.6), 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 coefficient of interest is the sum of the average effect and the interaction term between the shock and each decile. We interpret the

Figure 1.3: A Positive Credit-Supply Shock Reduces Wages in the Bottom Half of the Wage Distribution While Increasing Wages at the Top of the Distribution

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

result as the total effect on each wage decile.

Figure 1.3a shows the effect on impact while Figure 1.3b shows the effect one year after the shock. The horizontal axis shows each of the wage bins. For example, 10 represents workers in the 0–10 percentile, 20 is the group between 10 and 20, and so on. The vertical axis shows the estimated coefficient of the total effect of a positive credit-supply shock in the wage growth rate. On impact, we see a significant decline in wages below the median relative to wages on the top of the distribution. Similarly, wages on the ninth decile relatively increase relative to the mean. Wages of workers on the bottom of the distribution that receive a positive credit-supply shock of one standard deviation, decline by 7.8%. However, wages of workers on the ninth decile that receive an equivalent shock experience a wage growth of 2%. To put these numbers in context, the average growth rate of wages is 1.5%. This means that those at the top continue growing at a similar rate after the shock, but workers on the bottom receive less wages. The effect on the growth rate stops one year after the shock.

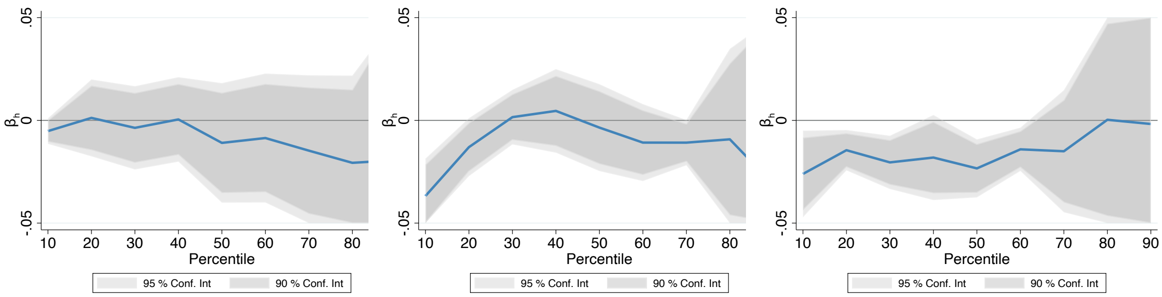
We show a temporary effect on the growth rate of wages. Now, we turn our attention to not the effect on each of the workers, but on the level of income: the cutoff values of each decile of income. Here, we seek to understand the effect of a credit-supply shock on the distribution. To do so, we estimate equation 1.6. Figure 1.4 establishes one of the paper's main empirical results. This time, the horizontal axis again shows each decile of income. The vertical axis shows the estimated coefficients for each decile's change in value. This exercise is important because we initially compared changes in wages of each of the groups of workers. Now, we study how the distribution changed. This allows for a recomposition of each decile. The result shows a lasting negative effect on below-median wages one and two years after the shock. This means that a one-time shock has a negative and temporary effect on the growth rate of wages but has a more permanent effect on the overall wage distribution. Figures 1.4b and 1.4c show that there is a negative effect on low-income wages. In particular, the effect on the lowest decile is negative and statistically different from zero with 95% confidence one year after the positive credit-supply shock. Moreover, the effect extends to the bottom half of the distribution two years after the shock. This means that the lowest decile declines 0.65% due to a one-standard-deviation positive credit-supply shock to the workers' firm. Wages below the median decrease 0.26% two years after the shock.[22]

We interpret a credit-supply shock's positive effect on the capital and negative

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

Figure 1.4: 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 (1.7) for $h = 0$. Panel **(b)** estimates it for $h = 1$ and Panel **(c)** for $h = 2$. The horizontal axis shows the wage deciles, and the vertical axis shows the change in each decile's cutoff value. Each regression has 6,150,523 observations for $h = 0$, 2,976,639 for $h = 1$, and 1,879,977 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

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

1.4.4 Uneven effect across firms: Liquidity constraints

So, a positive credit-supply shock creates a physical-capital investment opportunity and simultaneously drives the bottom half of the wage distribution down. However, if these firms face an investment opportunity, why do they not expand in scale? Why is demand only changing for some workers? One potential explanation is the role played by liquidity. Gilchrist et al. (2017), for example, find that the liquidity channel is important to understanding how firms respond to external financial shocks.

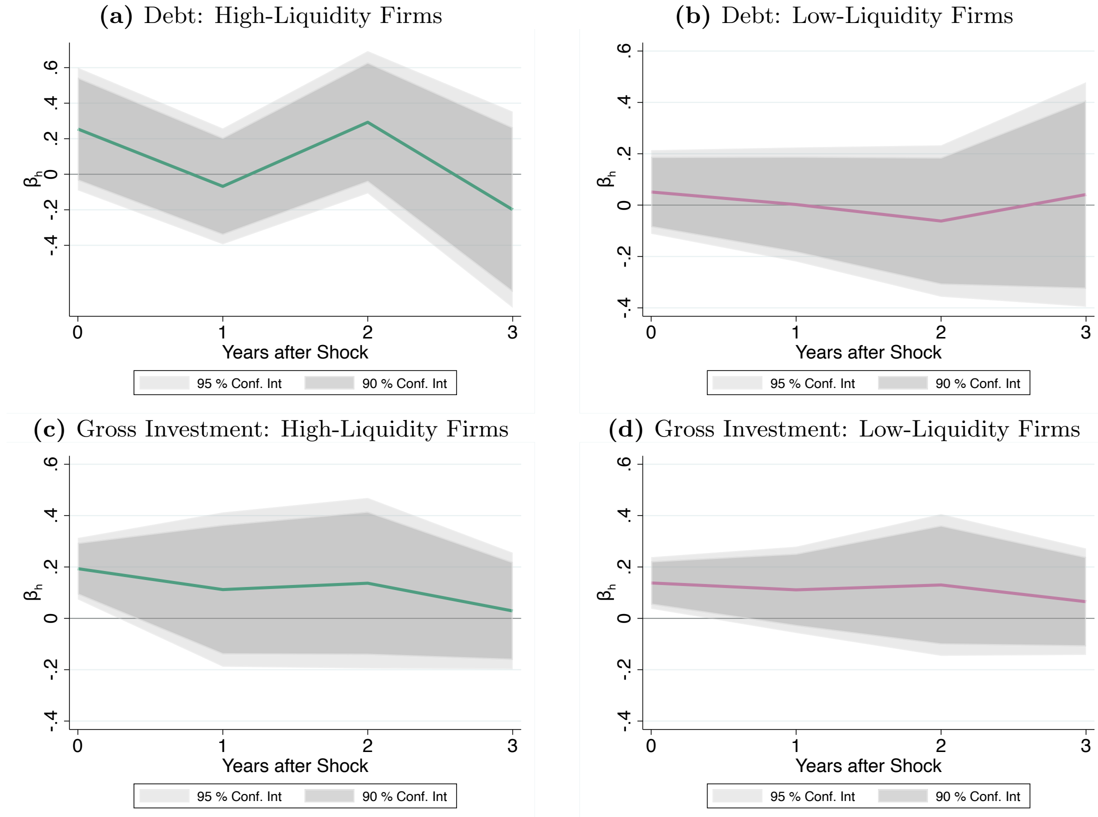
[23] Although this literature has focused on the job–skill polarization in developed economies (see Acemoglu and Autor (2011) for an extensive review), Medina and Posso (2018) find suggestive evidence that this is also a characteristic of the Colombian labor market.

To preserve the ability to finance all current obligations, instead of expanding in scale, firms could choose to substitute some types of workers when they increase their capital stock. In this section, we study firms' heterogeneous responses to a positive credit-supply shock based on their level of liquidity.

We split our sample between high- and low-liquidity firms. The former has an above-average ratio of cash and short-term investments to assets. Figure 1.5 compares the effects on debt and gross investment between high- and low-liquidity firms. We do not observe heterogeneity in terms of debt and investment. We interpret this result as evidence that a positive credit-supply shock creates a similar investment opportunity for all firm types.

In the presence of working capital constraints financed with liquid funds and a production function where capital and labor are complements—neoclassical production function—we should expect that firms with more cash holdings—less financially constrained—could increase of their labor demand more than financially constrained firms. The first two panels of Figure 1.6 compare the effect on employment between high- and low-liquidity firms. The effect of a positive credit-supply shock is positive and statistically significant for high-liquidity firms. The point estimate for low-liquidity firms is negative and not significant. This suggests that one potential channel to explain our results is the presence of internal working capital constraints to finance labor. In the seminal working-capital-constraints literature, firms finance labor with external financing (Quadrini, 2011; Neumeyer and Perri, 2005). Our evidence suggests that firms use external debt financing to invest. This new investment is only accompanied by higher labor demand if the firm has enough internal resources to finance an expansion in scale. Otherwise, labor demand seems to decrease.

Figure 1.5: Impulse Response Functions to a Positive Credit-Supply Shock on Debt and Gross Investment of Firms With Different Levels of Liquidity

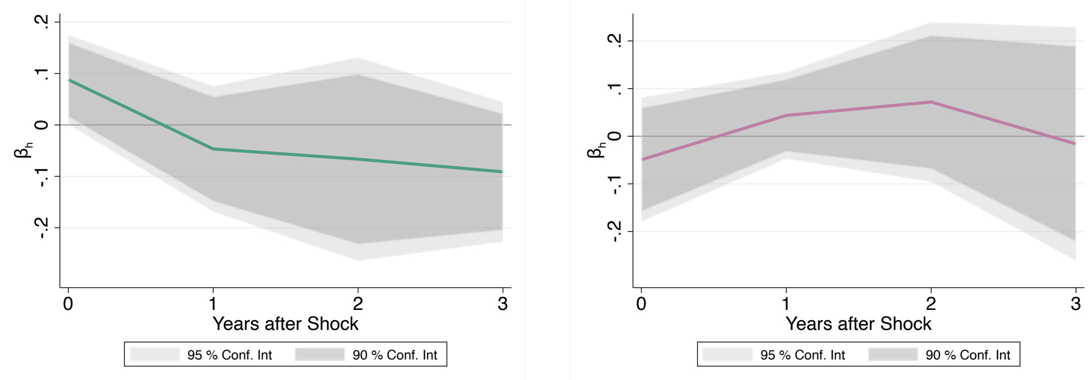


Note: Panels **(a)** and **(c)** show the estimated effect of a positive credit-supply shock on banking debt and gross investment using equation (1.5) for high-liquidity firms. Panels **(b)** and **(d)** show the estimated effect on banking debt and gross investment using equation (1.5) for low-liquidity firms. A high-liquidity firm has an above-average ratio of cash and show-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

Figure 1.7 compares the effect on working capital between high- and low-liquidity firms. We measure working capital as the ratio of short-term assets to short-term liabilities. This measure compares the amount of liquid funds with the current obligations. With a positive credit-supply shock, low-liquidity firms reduce their working capital on impact and it remains low a year after the shock. In contrast, the effect on working capital for high-liquidity firms is positive and statistically significant one and two years after the shock. This suggests that the new investment opportunity creates a trade-off for firms with low liquidity: to take the investment opportunity

Figure 1.6: Impulse Response Functions to a Positive Credit-Supply Shock for Employment of Firms With Different Levels of Liquidity

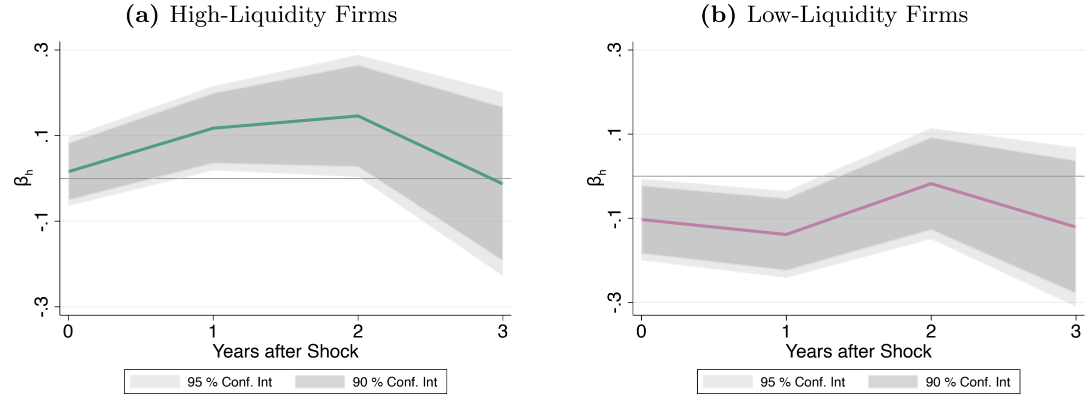
(a) High-Liquidity Firms **(b)** Low-Liquidity Firms



Note: Panel **(a)** shows the estimated effect of a positive credit-supply shock on employment using equation (1.5) for high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. A high-liquidity firm is a firm with an above-average ratio of cash and short-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

Figure 1.7: Impulse Response Functions to a Positive Credit-Supply Shock for Working Capital of Firms With Different Levels of Liquidity

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



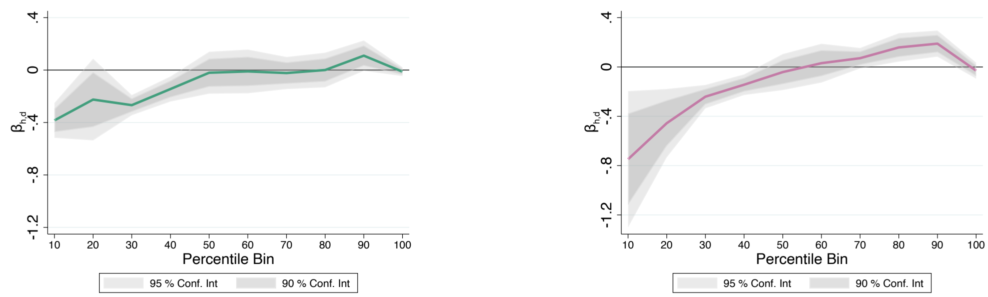
Note: Panel **(a)** shows the estimated effect of a positive credit-supply shock on working capital using equation (1.5) for high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. We measure working capital as the current-assets-to-current-liabilities ratio. A high-liquidity firm has an above-average ratio of cash and short-term investment to assets. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

they need to reduce their working capital, leading to a potential decrease in labor demand. High-liquidity firms do not face a trade-off and can expand in 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

Figure 1.8: Heterogeneous Response on Impact to a Positive Credit-Supply Shock for Workers' Wages From Firms With Different Levels of Liquidity

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



Note: Panel **(a)** shows the estimated effect of a positive credit-supply shock on wages in income bins using equation (1.6) for $h = 0$ in high-liquidity firms. Panel **(b)** shows the same for low-liquidity firms. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

on wage growth using equation (1.6). Figure 1.8 shows the effect on wage growth at impact. Panel 1.8a shows the effect for high-liquidity firms, while panel 1.8b shows the same for low-liquidity firms. As expected, the negative effect on the bottom half of the distribution is more pronounced for low-liquidity firms. We interpret this result as evidence of the trade-off between increasing the capital stock and increasing labor in the presence of liquidity constraints. When capital is a substitute for some types of labor, the firm might increase the capital stock but reduce demand for those workers who capital substitutes. As a result we observe wages of some workers going down, and labor demand only expanding for some firms. The magnitude of the effect is significant. In high-liquidity firms, wages in the bottom of the distribution decrease 5.3% after a one-standard-deviation shock, whereas low-liquidity firms' wages fall by 10%. This means that low-income workers in low-liquidity firms disproportionately lose with a positive credit-supply shock compared with the average worker and with the equivalent worker in a high-liquidity firm.

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

1.5 Model

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

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

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

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. Households own the firms and the banks and supply labor.

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

1.5.1 Household

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

The household's recursive problem is

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

subject to

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

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

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

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

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

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

1.5.2 Banks

The banks are owned by the household and pay dividends π^{B} every period. Banks take deposits m from the firms. The banks pay an exogenous gross interest rate $R^m > 1$ to the firms for their deposits. The bank only pays interest on the deposits

[25] We describe the search problem later in section 1.5.4.

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

that stay in the bank until the end of the term. To maximize the value of the banks, they choose loans to the firms d' every period. These loans are subject to an intermediation cost. The banks charge a gross rate $R > 1$ for each unit of debt that the banks take as given.

The banks recursive problem is

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

subject to

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

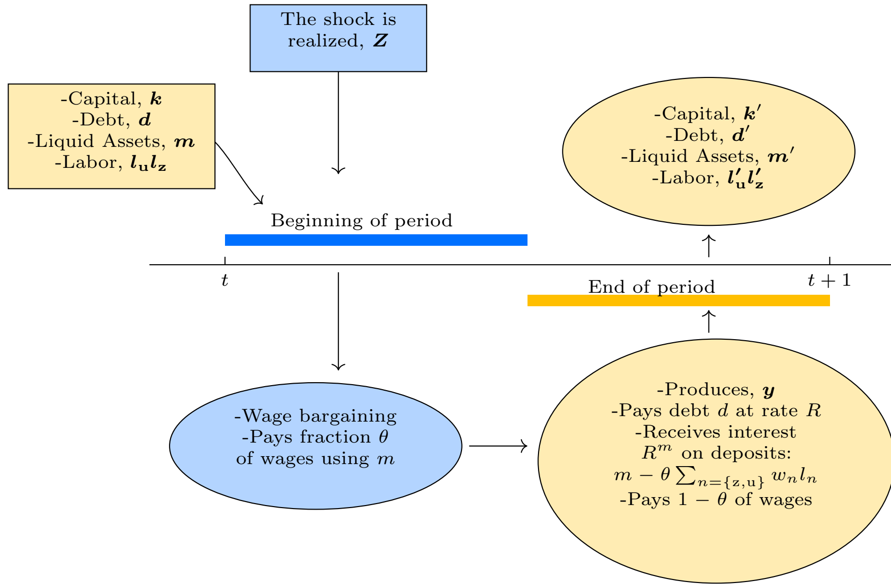
where $\theta(R^m - 1)\sum_{n=\mathrm{z,u}} w_n l_n$ corresponds to the early-withdrawn deposits of the firms that did not receive interest. $M(s'|s)$ is the household stochastic discount factor, and s is the aggregate state. $Z > 0$ is the lending intermediation cost of new debt and is the source of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

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

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

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

Figure 1.9: Timing of the Firm's Decisions During the Period



The functional form for the elastic debt supply follows

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

1.5.3 Firms

The firms produce a final good using capital and two types of labor. Each firm enters the period with capital k, debt d, liquid assets m in the form of deposits in the banks, and two types of labor: skilled l_{z} and unskilled l_{u}. We divide the decisions within the period in two parts. Figure 1.9 illustrates the timing of the firm's decisions during the period.

In the morning of the period, after the credit-supply shock is realized, the firm bargains wages w_{z} and w_{u} with the workers in two separate markets, 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 $\theta \sum_{n=\{\mathrm{z,u}\}} w_n l_n$ from its liquid assets deposited in the banks.

At the end of the period, production $y = f(k, l_{\mathrm{u}}, l_{\mathrm{z}})$ 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:

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

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

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

When adjusting debt or capital, the firm pays a quadratic adjustment cost. The firm chooses labor demand by posting vacancies v_n on each market n. Posting a vacancy on each market has an exogenous cost ζ_n. Every period, an exogenous fraction of workers ρ_n loses 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

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

subject to

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

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

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

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

The first term represents nonroutine activities that are only realized by skilled workers. The second term of the production function represents the routine activities. These activities can be realized either using capital or low-skilled labor. Given this production function, two parameters are key to understanding the effect of the credit-supply shock on wages. One is the substitution parameter between nonroutine and routine activities, η_a. The other is the substitution parameter between capital and low-skilled labor. η_r.

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

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

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

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

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

1.5.4 Search and wage bargaining

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

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

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

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

$$1 = l_n + u_n$$

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

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

where $\mu_\mathrm{u} \in [0,1]$ is the workers' bargaining power. λ_{1f} is the Lagrange multiplier of the liquid-assets constraint from the firms' optimization problem. It is important to notice that to guarantee a solution, the firm always must have enough deposits to pay wages. $\tilde{V_n}(w_n)$ is the marginal benefit to the household for having an extra worker employed at the current level of consumption, savings, and rate of unemployment. $\tilde{J}(w_n(\lambda_{1f}))$ is the value of the firm for hiring an extra worker at the current firm conditions. We derive $\tilde{V_n}(w_n)$ and $\tilde{J}(w_n(\lambda_{1f}))$ in Appendix A.3.1. Our solution is equivalent to the canonical search model in Shimer (2010).

1.5.5 Equilibrium and discussion of the mechanisms

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

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

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

Recall that $\mathbb{E}M(s'|s) = \beta\mathbb{E}\frac{u_1(c',l'_\mathrm{z},l'_\mathrm{u})}{u_1(c,l_\mathrm{z},l_\mathrm{u})}$ is the stochastic discount factor from the household problem. We interpret $\frac{1}{M(s'|s)}$ as the return on savings for the household.

This means that a reduction of the borrowing cost reduces the gap between the household savings rate and the firms' borrowing rate.

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

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

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

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

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

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

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

where λ_{f1} is the Lagrange multiplier for the money-holdings constraint. Because R^m is fixed, when the constraint binds, a reduction in the intermediation cost increases the shadow cost of liquid asset holdings, λ_{f1}. This effect has an immediate implication for labor demand. Because firms use liquid assets to finance working capital, increasing debt demand depresses labor demand. After the Nash bargaining process, labor demand comes from

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

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

where MPL_{u} and MPL_{z} are the marginal products of labor of unskilled and skilled workers, respectively. In Appendix A.3.1 we solve for the wage bargaining problem in detail.

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

Second, when the firm is constrained, $\theta > 0$, a positive credit-supply shock reduces the firms' money holdings, and tightens the constraint, 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, two opposing forces determine labor demand for skilled workers—the capital–low-skill substitutability or the working-capital constraint. The total effect will depend on which effect dominates. In terms of average wages and employment, the effect is also ambiguous. Average wages can increase if labor demand for unskilled workers substantially decreases.

1.5.6 Quantitative analysis

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 A.7 in the appendices). Note that the shock is not very persistent, and it is highly volatile.

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

We calibrate the deposit rate using the average fixed-term deposits rate with annual maturity. Then, we set $R^m = 1.0261$. We equate the discount factor to the inverse of the interbanking rate, the rate for credit operations between banks. Since our model requires $1/\beta$ to be the median rate in the market, we use the fifth percentile of the interbanking rate during 2008–2018 and set $\beta = 0.9598$. Notice that this number is close to the calibration in Neumeyer and Perri (2005) for the Argentinian economy. Finally, we set the steady-state borrowing rate to match the average corporate-credit borrowing rate. Table A.8 in the appendices reports summary statistics for these three rates.

We use data from the firms' financial reports and some aggregate data at the national level for the firms' parameters. The key targeted moments in our model are the steady-state debt-to-capital ratio, $\frac{d^*}{k^*}$, and the on-impact effect on investment and debt. To match these moments, we measure $\frac{d^*}{k^*}$ as the average leverage (See Table 1.1). We set κ to match the effect on debt and investment. We calibrate $\bar{d}$ and Z^* to satisfy the firms' and banks' steady-state Euler debt equations. Since the volatility of investment is determined in the model by the portfolio-adjustment costs and $\frac{d^*}{k^*}$, we set 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 A.9). For the production function, we use the same parameters in Vom Lehn (2020). To evaluate the role of the working capital channel, we use $\theta = 1$, assuming that the firm must pay all of its wage bill before production takes place.

Because we do not observe hours or additional characteristics in the data, we follow the literature to set the household parameters. The key parameter in our model is the elasticity of labor supply. Neumeyer and Perri (2005) use an intermediate value between Mendoza (1991) and Correia et al. (1995). It is important to highlight that the implied value of the elasticity of labor supply of these papers (1.66) is large. Restrepo-Echavarria (2014) and Alberola and Urrutia (2020) use an inelastic labor supply to study the role of informality on developing economies and Mexico specifically. We use the estimates in Prada-Sarmiento and Rojas (2009) for the elasticity of

Table 1.4: 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 avg. leverage
Portfolio-adjustment costs	κ	0.9	Match estimated debt
Investment-adjustment costs	ϕ	0.5	Match estimated debt
	Colombian aggregate data		
Discount factor	β	0.9241	Inverse p5 interbank rate
Steady-state int. cost	τ	0.1053	Diff. corp. and borrowing rate
Steady-state unemployment rate	$\bar{u}_n$	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.
Steady-state probability of filling a vacancy	$\bar{q}(\theta_n)$	0.7	Standard lit.

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 posting a vacancy, ζ_n, and the probability of unemployment, ρ_n, in each market to match the average unemployment rate in Colombia during the sample period of 10.02% and the steady-state probability filling a vacancy of 0.7. We set the Nash bargaining parameters, μ_{u}, and the matching function parameters, ϕ_0 and ϕ_1, all to 0.5. Table 1.4 summarizes our calibration.

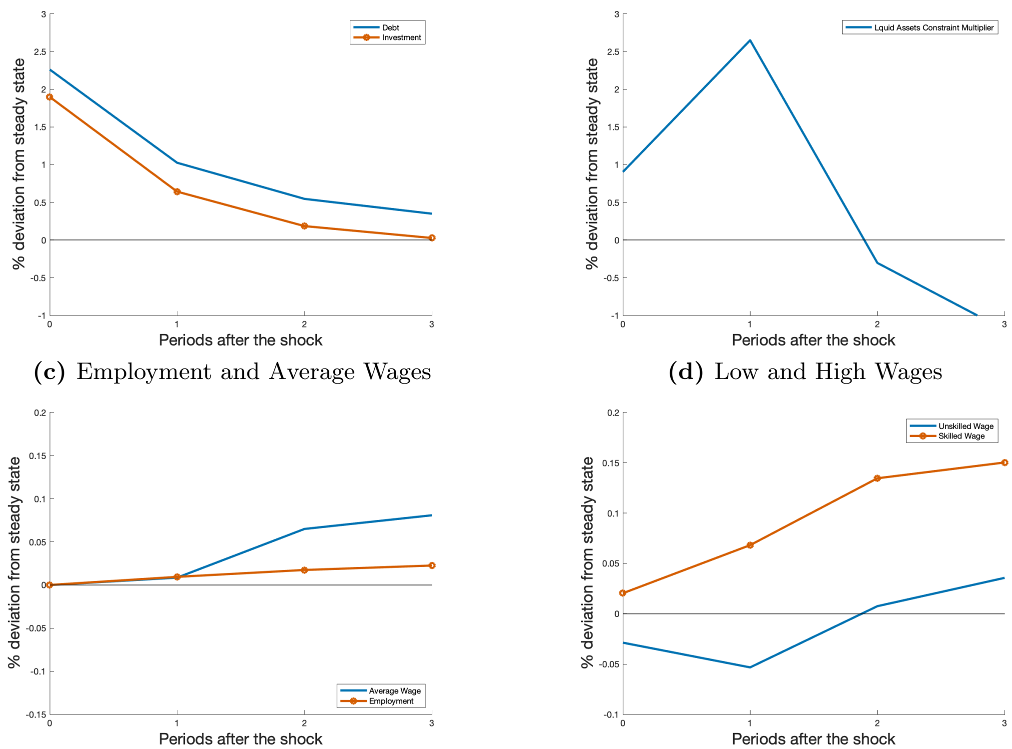
Simulations

To compare the model with the data, we focus on the impulse response functions of debt, gross investment, employment, average wages, and wages by type of worker. Recall, to keep the model simple, we understand unskilled wages as equivalent to wages below the median income in the data, and skilled wages as wages above the median. We start by simulating the baseline model. For these results we assume that the constraints always bind. Figure 1.10a shows the effect on debt and gross investment. The horizontal axis in this figure shows the periods after the shock. The vertical axis shows the percentage response to a one-standard-deviation shock. Recall that we calibrate the shock to have the same persistence as the estimated shock in the data. As we discussed before, we target the response of debt to match the estimates' response in the data. All the remaining effects in the model are results. As we expected, in response to a positive credit-supply shock, the capital stock increases by 2%, which is very close to the change of 1.8% in the data. Figure 1.10b shows the effect on the shadow value of holding money. With this figure, we want to highlight the trade-off firms face. A positive credit-supply shock increases the opportunity cost of holding liquid assets and the benefit of investment. Figure A.6 in the appendices shows the effects on the borrowing interest rate and money holdings.

Figures 1.10c and 1.10d show the labor market results. Figure 1.10c shows the effect on employment and average wages. The model predicts a small positive effect on both average wages and employment. These two results are consistent with our empirical findings. The model, however, predicts a larger effect on average wages two and three periods after the shock. The reason for this discrepancy is that, compared to

Figure 1.10: Impulse Response Functions to a Positive Credit-Supply Shock of Investment, Debt, Wages, and Employment

(a) Debt and Gross Investment **(b)** Shadow Value of Liquid Assets **(c)** Employment and Average Wages **(d)** Low and High Wages



Note: Impulse response functions for the baseline model simulations.

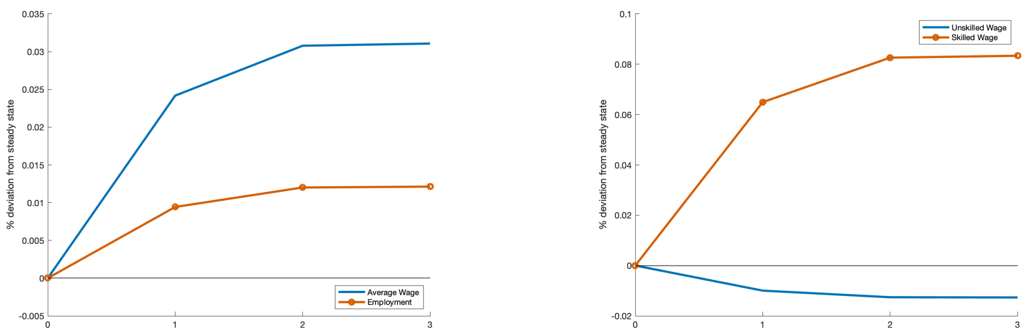
the data, demand for high-skill workers is more responsive to a positive credit-supply shock. Figure 1.10d shows the effect on wages by type of worker, demonstrating how both mechanisms interact. On impact, similarly to Figure 1.3 in the empirics, wages of low-skilled workers decline, while those of the high-skilled workers increase. The negative effect lasts for two periods for low-income workers, while it becomes positive for high-income workers. In other words, one period after the shock, working capital dominates the production function. As the liquid-assets constraint becomes binds less, the effect of capital–skill substitutability takes relevance. The key parameter to determine which effect dominates one period after the shock is the elasticity of substitution between capital and low-income workers. As low-income workers substitute for capital more exactly, the negative effect on low-income workers disappears. Figure A.7 in the appendices shows the sensitivity analysis for capital–low-skilled substitutability. This parameter is of particular relevance for the effect three years after the shock.

To understand the effect of a positive credit-supply shock on unconstrained firms, we simulate the model with no working capital (Figure 1.11). One point to emphasize is the magnitude of the change in debt and investment compared with the baseline model (see Figure A.8 in the appendices). As with the data, our unconstrained firm is as responsive as the constrained firm in terms of debt and investment. Figure 1.11a shows the effects on average wages and employment. Contrary to what we observe with the baseline model, average wages decrease and employment increases for two reasons. First, Figure 1.11b shows the effect on low-skilled and high-skilled wages. Similarly to the data, the negative effect on low-income workers is half of the constrained firm's effect. Moreover, the effect on high-skilled wages is also larger. As a result, both employment and average wages increase more compared to the constrained firm's results. In other words, because the firm faces a trade-off between increasing capital and using liquid funds to pay for the working capital, we only observe the effect of the capital–low-skilled substitutability channel.

Finally, we explore the effects of a positive credit-supply shock on a firm with just one type of labor and a working-capital constraint (Figure 1.12). 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. This suggests that the small changes in

Figure 1.11: Impulse Response Functions to a Positive Credit-Supply Shock to Wages and Employment for Firms With no Working Capital

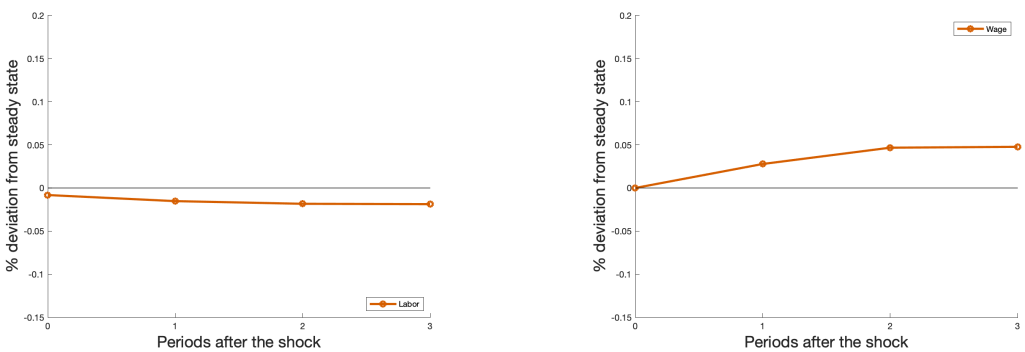
(a) Employment and Average Wage **(b)** Wages



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

Figure 1.12: Impulse Response Functions to a Positive Credit-Supply Shock for Wages and Employment in Firms With Only One Type of Labor

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



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

average wages and employment could potentially be explained by the interaction of the two mechanisms. These two forces eliminate the effect on labor demand for high-income workers, so we only observe changes at the bottom half of the distribution in the data.

Counterfactual

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

Our experiment consists of reducing $\bar{\tau}$ by 20%. A reduction of 20% in $\bar{\tau}$ is equivalent to reducing the steady-state borrowing rate from 8% to 7%. Figure 1.13 compares the impulse response functions of the baseline model with that of the counterfactual. Panel 1.13a compares the effect on average wages and employment, Panel 1.13b shows the effect on skilled and unskilled wages. The result shows that when the intermediation premium is permanently smaller, low-skilled wages do not decrease as much as they do in the baseline model. For instance, one year after the shock, low-skilled wages are 5.93% higher compared to the baseline model. High-skilled wages, on the other hand do not increase as much as in the baseline model. One year after the shock, high-skilled wages are 8.3% lower compared to the baseline model. As a result, the response to a credit-supply shock of average wages and employment is even smaller when the intermediation premium is permanently lower.

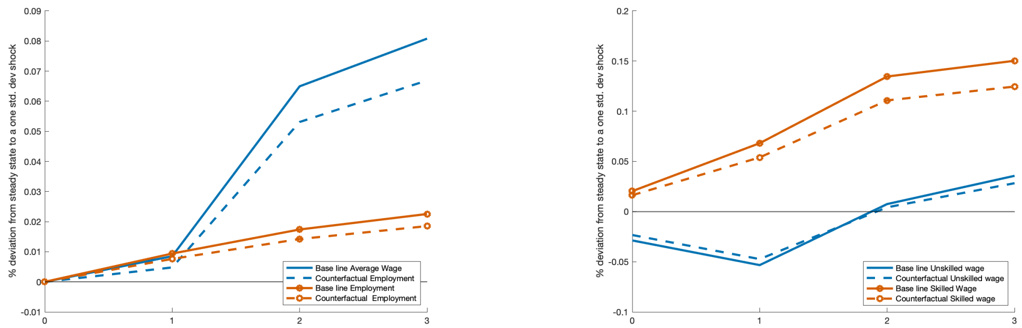
This means that reducing the intermediation premium helps reduce the wage gap between skilled and unskilled workers. However, two and three years after the shock, the firm does not increase high-skilled wages as much compared to the baseline model. This translates to lower average wages and also lower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

The mechanism works as follows. By improving the bank's ability to turn deposits

Figure 1.13: Comparing the Impulse Response Functions of a Positive Credit-Supply Shock on Employment and Wages for Different Levels of a 20% Lower Intermediation Premium

(a) Employment and Average Wage

(b) Wages



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

into firm debt, the debt supply becomes less responsive to an equivalent shock (see Figure A.9a in the appendices). Thus, in response to a positive credit-supply shock, debt increases four percentage points less than in the baseline model. This translates to a smaller increase in the capital stock: The investment opportunity is not as great (see Figure A.9b in the appendices). From the capital—skill-substitutability channel, the firm does not decrease demand for unskilled workers compared to the baseline model. At the same time, the trade-off between investment and holding liquid assets goes down one period after the shock (see Figures A.9c and A.9d in the appendices). As a result, we observe that employment and average wages do not decrease as much compared to the baseline model. However, since the firm did not increase its capital stock, the long-term effect hurts high-skilled workers, employment, and average wages. In this sense, when we reduce the intermediation cost by making banks more efficient, the liquidity constraint becomes less relevant in the long run.

1.6 Conclusions

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

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

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

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

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

CHAPTER II

A North-South Model of Structural Change and Growth

with John Leahy and Linda Tesar

2.1 Introduction

In response to the spate of balance of payments crises of the 1980s, then U.S. Secretary of the Treasury James Baker articulated a plan of structural reforms to promote growth in low and middle-income countries and increase their access to international financial markets. The nexus of policy reforms around fiscal and monetary discipline, privatization, and openness to foreign investment were largely endorsed by the IMF, the World Bank and the U.S. Treasury and came to be known as the "Washington Consensus" (Williamson, 2018). While there may have been a consensus about the merits of the recommended policy agenda in the early 1990s, there is less agreement today about the success of the policy agenda as it was put into practice. Critics point to evidence that the policies failed to produce a sustained increase in the rate of economic growth in low income countries (Rodrik, 2006; Goldfajn et al., 2021; Zagha et al., 2005). Further, they argue, there is evidence to suggest that those countries that reformed later, at the wrong point of their growth cycle, or with weak institutions, may lose from liberalization (see, for example, Rodrik (2016); Stiglitz (2000). Other economists, however, are more optimistic, noting that in the period following the implementation of policy reforms, countries experienced a spurt of investment, a decline in the cost of capital and an increase in capital inflows (Chari et al., 2021; Henry, 2007). The Summer 2021 issue of the *Journal of Economic Perspectives* devotes 90 pages to a post-mortem of the Washington Consensus.

Our paper provides a reconciliation to these seemingly contradictory perspectives – at least in the evaluation of the impact of capital market liberalization – when viewed through the lens of a neoclassical model of growth and structural change. We begin by documenting patterns of investment, income and structural change in 34 countries over a span of six decades. In order to focus on the general features of rich and poor countries and avoid an overemphasis on the special experiences of a few countries, we split our set of countries into two groups: advanced economies (with per capita income above the sample median at the beginning of our sample) and emerging markets (those with per capita income below the median). Our first main empirical result is that prior to global capital market integration in the early 1990s, the two groups of countries follow roughly identical trajectories of growth and structural change, with the emerging markets starting later in time and at a lower level of per capita income. Advanced economies experience a peak in the investment rate in the mid-1970s at 26 percent of GDP. The parabola that is fitted to advanced economies for 1960 to 1991 also fits the data for emerging markets, with a rightward shift in time or a leftward shift in per capita income. Using that parabola, the model predicts that emerging markets would reach their peak investment rate at 26 percent of GDP in 1991. Most theories link the investment to GDP ratio to the structure of production across manufacturing, services and agriculture, with investment tied to the share of manufacture. We document the change in the composition of GDP over time in our two regions and find that these too are remarkably similar, although the transformation in emerging markets appears to lag that of developing nations by a bit longer than does the peak in investment relative to GDP.

Our second main empirical result is that when we consider data from the 1990s and beyond, the investment to GDP ratio in emerging markets flattens out and remains elevated relative to the path that had been followed by the advanced economies. This high investment rate corresponds to a period of capital market liberalization. At the same time that investment is elevated, we see a significant increase in the flow of private investment from advanced economies to emerging markets.

To better understand these patterns in the data, we develop a two-region model of the world economy. To generate the observed rise and fall in the ratio of investment to GDP we include three goods – agriculture, manufacturing and services – and model the transition from agriculture to services as the economies grow. In the model, this transition is driven both by time-varying preferences and by differences in the production structure and technological growth across sectors. Consistent with the observed similarity in development across the two regions, the model explains the development experience of the two regions remarkably well with very similar specifications for the two regions. In the model the two regions share the same technology and preferences and differ only in that the emerging market group starts its growth process at a later point in time, at a lower level of per capita income, and have slightly different efficiencies at the sectoral level. We assume that the regions are isolated from each other up to the point of capital market liberalization in the early 1990s. At that point, capital flows from advanced economies to emerging markets, equalizing the return on capital and pushing the emerging markets further along their growth path. In effect, capital market liberalization redistributes capital between the two regions, resulting in transitory changes in investment and output, but does not alter the underlying process of growth. In this sense, the model is consistent with what both the critics and supporters of the Washington consensus have observed: private capital flows spur investment and lower the cost of capital, but do not produce a sustained increase in long-run growth. Consumption levels change permanently, however, due to the dynamics of borrowing in the short run and debt service in the long run.

Our model allows us to evaluate the gains from capital market liberalization. We find that both regions gain from the liberalization of financial markets, but the majority of the gains accrue to the emerging economies. The overall magnitude of the gains depends on the date of liberalization, the relative sizes of the two regions and the degree of asymmetry between the two regions at the point of liberalization. Emerging markets prefer to liberalize earlier, and their share of the gains is larger the earlier the date of liberalization. This makes intuitive sense, as the gains from liberalization are greater the larger the difference between the cost of capital in the two regions, and this difference shrinks as the two regions converge toward their long-run steady state.

Our group of emerging markets does not include China. For most of the sample, China plays a minor role in the world economy, but this role has grown quite significantly as of late. We therefore perform a counterfactual to examine the effect of China's full integration into global capital markets. We assume that China allows unfettered private investment inflows in 2020. Given our assumption that the marginal product of capital in China at the point of opening is higher than the prevailing global interest rate, the gain from this new investment opportunity is unambiguously positive for advanced economies. The impact on emerging markets, however, is more nuanced. Those that enter this second wave of liberalization encumbered by debt from the first liberalization may actually suffer a welfare loss, as the cost of debt service exceeds the gains from investing in China.

Related literature

A key contribution of our study is to develop a quantitative model that is consistent with the dynamics of saving, capital accumulation, and sectoral shares within countries, as well as with the global allocation of investment in emerging and advanced economics. Our model builds off the work of Echevarria (1997), one of the earliest quantitative models of structural transformation in a closed economy. Her model combines the two mechanisms that have proved important in the subsequent literature. The first mechanism works on the demand side by assuming that preferences are non-homothetic. Non-homothetic preferences help explain patterns of expenditure as income rises, in particular the shift in spending from agricultural goods to manufacturing and services. Such preferences take many forms. Kongsamut et al. (2001) and Moro (2015) use Stone-Geary preferences, Foellmi and Zweimüller (2008) use hierarchical preferences, and Comin et al. (2015) use generalized CES preferences. Boppart (2014) uses the class of price independent generalized linearity preferences.

We capture these non-homotheticities by assuming that preferences are time varying and converge to Cobb-Douglas.

The second mechanism works on the supply side. Echeverria allows for differences across sectors in the rate of technological progress and factor intensity in production. Both of these mechanisms can lead to trends in relative prices that can, in turn, shift demand across sectors. Both supply-side and demand-side mechanisms can generate hump-shaped dynamics in the share of manufacturing production in output. Ngai and Pissarides (2007) emphasize differences across sectors in TFP growth, while Acemoglu and Guerrieri (2008) explore differences in factor utilization. Alvarez-Cuadrado et al. (2017) consider differences in substitutability between capital and labor. Herrendorf et al. (2015) fit a model with all three supply-side mechanisms to US data. We follow Echevarria (1997) and include both differences in TFP growth and differences in factor intensity.

The literature on structural change and economic growth is large (see Herrendorf et al. (2015) for a review) and much of the work on growth has tended to treat each country as a closed economy or, if open, where trade is assumed to be balanced. Our contribution is to study growth and structural change in an environment with integrated financial markets. Seminal work in this area includes Ventura (1997) and Matsuyama (2009), who construct theoretical models that illustrate how structural transformation in open economies may differ from structural transformation in closed economies. Much of the recent work has focused on explaining the sustained growth of East Asian economies, in particular Korea (Uy et al., 2013; Cai et al., 2015) Many of these papers assume balanced trade and abstract from capital accumulation (Uy et al., 2013; Świkecki, 2017; Sposi, 2019). Recently, Kehoe et al. (2018) develop a global model of structural change with non-homothetic preferences, and multiple sectors to explain the decline of the US employment decline in manufacturing.

Capital flows are the main mechanism linking regions in our model. Opening financial markets allows capital to seek higher returns thereby promoting growth and accelerating the process of structural change. Technological progress is exogenous in our model. One can also imagine growth and structural change being driven by technology transfer. Fujiwara and Matsuyama (2020) explore such a model. In their model, there is no trade. Growth and structural changes arise as emerging economies adopt technologies developed by advanced economies.

Lewis et al. (2022) deserves special note. Like our paper, they consider a multi-country model of growth and sectoral change which they fit to a sample of 28 countries. They find that sector-based productivity growth alters relative prices and helps to explain deindustrialization in some emerging economies. Their study complements ours nicely. Whereas we focus on intertemporal trade and shut down comparative advantage, they focus on comparative advantage and assume intertemporal trade is largely exogenous.

The facts that motivate our study have predecessors elsewhere. The pattern of structural change is well known. The hump-shaped pattern in the investment rate has been noted by Echevarria (1997), Acemoglu and Guerrieri (2008), and Garcia-Santana et al. (2016). Rodrik (2016) and Fujiwara and Matsuyama (2020) argue that many emerging economies industrialize and de-industrialize at lower levels of GDP per capita than did advanced economies. What is new is our attempt to deal with all of these observations in a single setting and to explain the role of capital market integration on long-run growth paths.

2.2 Four Facts describing Investment, Economic Growth and Structural Change

In this section we establish four key facts describing the process of economic growth and structural transformation in a large sample of countries focusing mainly on the post-WWII period. We will return to these four facts in Section 3.2 to evaluate how well our model performs in explaining growth and sectoral change over time and across countries.

Our sample includes 34 countries. Together, these countries account for 82 percent of world GDP and 95 percent of world investment in 1960. We draw information from the Penn World Table 9.1, the World Development indicators, the Madison Project Historical National Accounts for the period 1930-1960, and the Federal Reserve Bank of St. Louis (FRED). Details regarding the data sources and the data construction are available in Appendix A.

We group countries into two regions based on per capita income in 1950. We place the rich countries into Block A, the global "North" in North-South models of growth and development, and the poor countries into Block B, the "South". We choose to group countries for two reasons. One is theoretical. A two country model delivers greater analytic clarity and tractability. The second is empirical. We wish to focus on the common trends that differentiate these groups rather than the idiosyncratic heterogeneity that is surely present. We comment throughout how these common trends relate to the individual experiences of various individual nations. We also consider several extensions of our model that incorporate heterogeneity in simple ways. The cost to our approach is that we abstract from differences across developing countries, especially differences between Latin America and East Asia that are the focus of other studies.

We choose to group nations based on income because income is the single most informative variable with regards to development. We do not want to sort countries based on the facts described below, since we want to show that these characteristics are characteristics of rich and poor nations. The one exception to the general rule is Japan, which was relatively poor following WWII, but grew very quickly thereafter. As Japan looks more like a rich country for most of the sample, we include it in Block A. Where appropriate we discuss the sensitivity of our results to the assignment of countries to the two Blocks. The main place that this matters is in the welfare results of Section 2.6.

Block A includes a set of advanced economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and United States. Block B includes the following emerging markets: Argentina, Brazil, Chile, Greece, India, Indonesia, Ireland, Malaysia, Mexico, Poland, Portugal, South Korea, Spain, Taiwan, Thailand, and Turkey. China is the most important country missing from this list. China plays a small role in the global economy at the beginning of the sample, but a larger role recently. We do not include China in our initial model becuase for most of the same it was not a market economy. In section 2.7, we consider the implications of integration with China for the global allocation of capital and welfare.

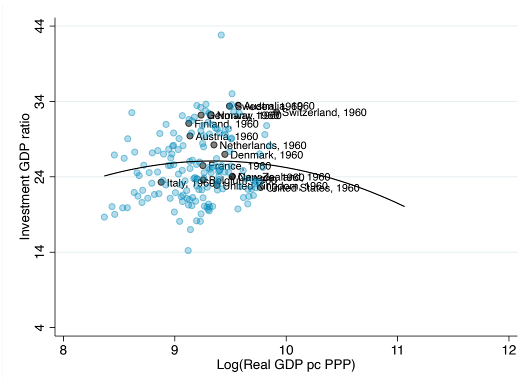
Where possible we define region level variables as the sums or averages of country level variables. Missing observations occasionally create complications. Details regarding the aggregation of country level observations to the block level are contained in Appendix B.1.

The first feature of the data we wish to highlight is the hump-shaped pattern in investment rates, both within countries over time and across countries. Figures 2.1a through 2.1d illustrate the evolution of the investment rate in Block A as real per capita income (PPP adjusted) rises over time. Each circle corresponds to an investment rate for a single country i in year t. Larger countries are associated with larger circles. Figure 2.1a shows investment rates for the early part of our sample (the decade 1950 to 1960), with the last observation of the decade as the darker circle, identified with a country label. This illustrates an increase in investment rates along with the increase in real per capita income. Figures 2.1b, 2.1c, and 2.1d extend the sample through 1980, 2000 and 2017 respectively. The circles become darker with each decade over time, and the darkest circles depict the last observation. The investment rates trace out a parabola that peaks in 1975 at a real per capita income of $19,000 (in PPP adjusted terms). This nonlinear relationship between investment rates and income, rising at low levels of income and then declining at higher levels of income, has been noted in other studies (see, for example, Echevarria (1997), Acemoglu and Guerrieri (2008), and Garcia-Santana et al. (2016)).

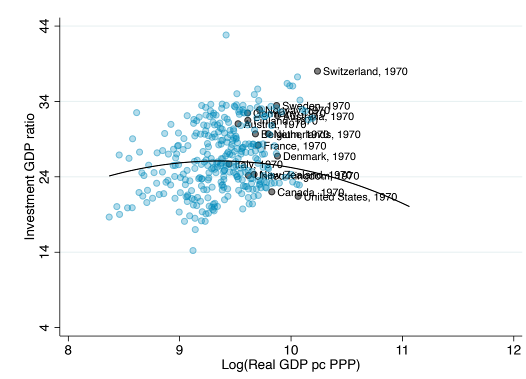
The hump-shaped pattern in investment rates observed for Block A is also observed in Block B. Figure 2.2 plots the investment rate for each region against time. The blue dots indicate the investment rate in Block A in each year. The solid blue line is a parabola fitted to these points. The red dots and the dotted red line depict the investment rate in Block B. Each region has a hump-shaped pattern in investment. The rise and fall in each block has a similar shape. The main difference is that the rise and fall in Block B occurs later in time. This is suggestive that the two groups of countries follow a similar investment trajectory as they grow, but they start different

Figure 2.1: Evolution of the investment rate in Block A

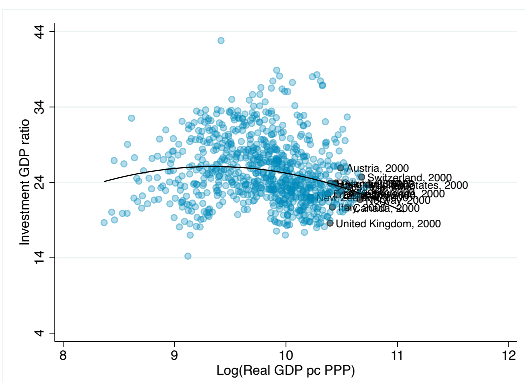
(a) 1950-1960



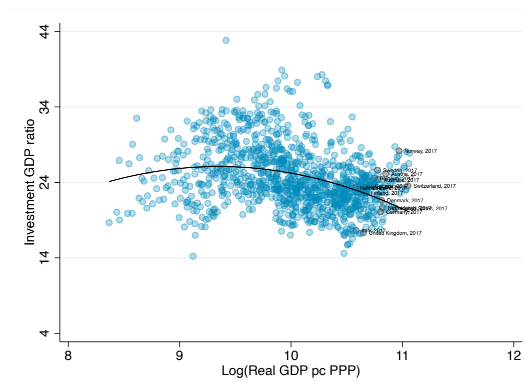
(b) 1950-1980



(c) 1950-2000



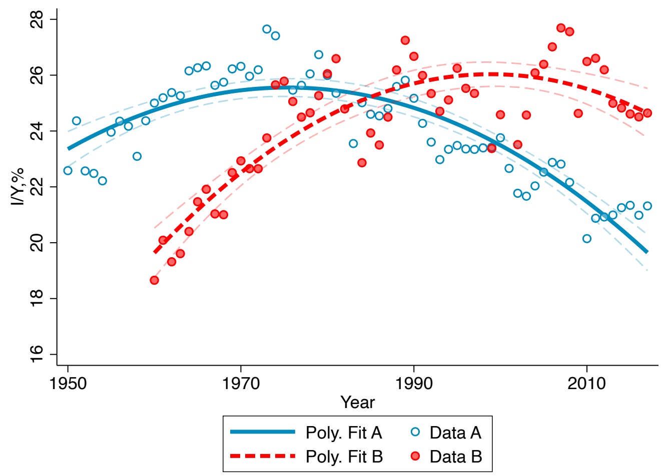
(d) All sample



Note: Each dot corresponds to a country in Block A in year t. Data Source: PWT9.1. The solid Lines corresponds to the fitted value of: $\frac{I_{iAt}}{Y_{iAt}} = \beta_0 + \beta_1 \log(GDP_{iAt}) + \beta_2 \log(GD_{iAt})^2 + \epsilon_{iAt}$

points in time. Table 2.1 makes these points precise. The table provides summary statistics on investment and income in the two regions. The first column shows that the fitted parabola's peak at very similar investment rates. The third column shows that this peak occurs several decades later in Block B.

Figure 2.2: Investment rate for each region against time



Note: Each dot corresponds to an observation in Block j in year t. We compute the investment ratio as total investment over total GDP in all countries in Block j, and GDP per capita as total GDP over total population in Block j. We use data from 1950-2017 for Block A and from 1960-2017 for Block B. Data Source: PWT9.1. Doted Lines correspond 95% robust confidence intervals: $\frac{I_t}{Y_t} = \beta_0 + \beta_1 Year + \beta_2 Year^2 + \epsilon_t$

Table 2.1: Summary Statistics: Fitted parabola for each region

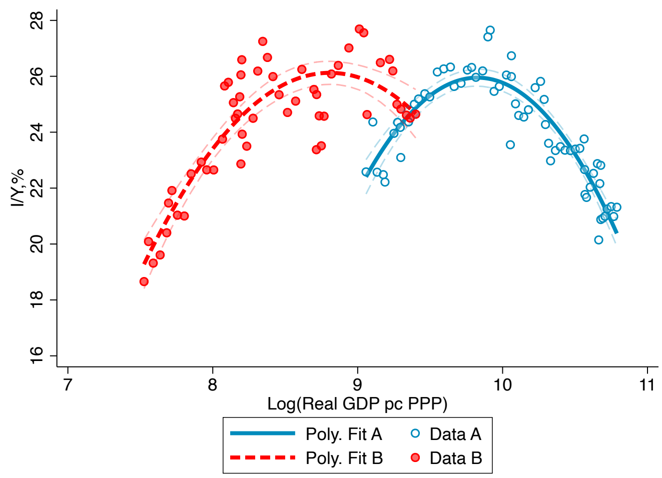
	$\max \widehat{I/Y\%}$	*Real GDP*	$Year$
Block A	25.5	19,773	1975
	(0.2)		
Block B	25.9	6,056	1998
	(0.2)		

Note: SUR standard errors in parenthesis. Data Source: PWT9.1. ° Real GDP *per capita* in PPP Expenditure side (2011 US dollars). Columns 4-6 correspond to the estimated coefficients of the $I_{jt}/Yjt = \beta_0 + \beta_1 Year + \beta_2 Year^2 + \epsilon_{jt}$

The similarities illustrated in Figure 2.2 mask two important differences between the blocks. The first important difference is that, whereas Block B peaks later in time, it peaks at a lower level of per capita income. Figure 2.3 transforms the x-axis in Figure 2.2 replacing each year with per capita (PPP adjusted) income in that year.

Again the curves represent parabolas fitted to the data. As is clear in the figure, investment peaks at a higher level of level of per capita income in Block A.

Figure 2.3: Investment rate for each region against per capita (PPP adjusted) income

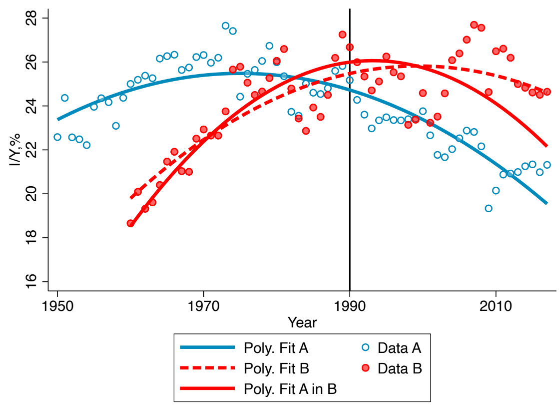


Note: Each dot corresponds to an observation in Block j in year t. We compute the investment ratio as total investment over total GDP in all countries in Block j, and GDP per capita as total GDP over total population in Block j. We use data from 1950-2017 for Block A and from 1960-2017 for Block B. We exclude years of sudden-stop recessions using the methodology in Calvo et al. (2006b) (1975, 1982 and 2009 for Block A, and 1983, 1998, and 2001 for Block B). Data Source: PWT9.1. Dotted lines correspond to 95% robust confidence intervals: $I_{jt}/Yjt = \beta_0 + \beta_1 \log(GDP_{jt}) + \beta_2 \log(GD_{jt})^2 + \epsilon_{jt}$

The second important difference between the regions is that the humps, while very similar, are not exactly the same shape. Figure 2.4 reproduces Figure 2.2, but instead of fitting a parabola to the investment rates for Block B, we translate the parabola from Block A until it fits Block B's data over the 1960 to 1991 period. While new curve fits the data well over this period, it underpredicts investment in the years that follow. This indicates that Block B followed a trajectory very similar to that of Block A until around 1991. Thereafter investment in Block B has been slightly higher than predicted by Block A's experience.

This period of relatively high investment in Block B coincides with an increase in capital flows from Block A to Block B. There was a surge in private capital flows

Figure 2.4: Investment rate for each region against time using different polynomial fits

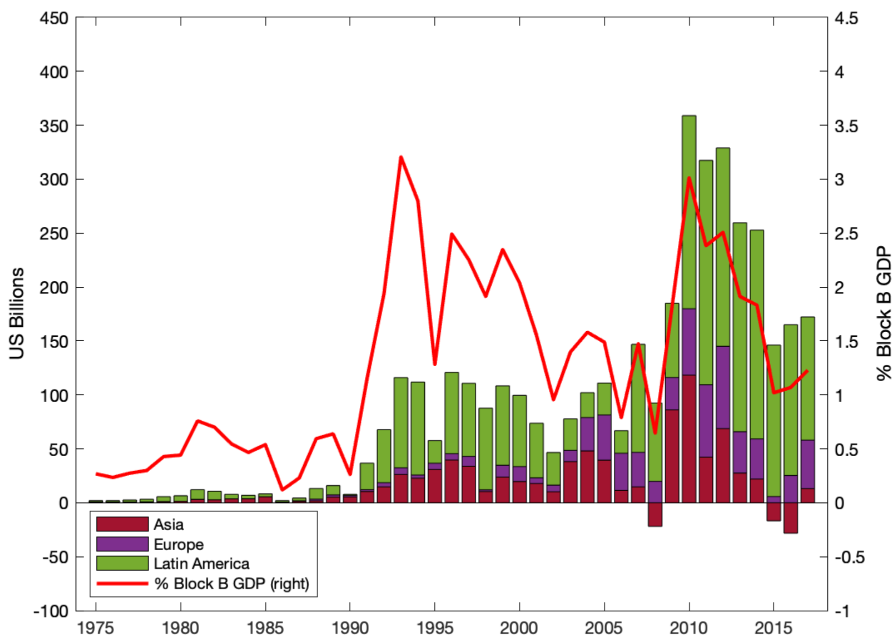


Note: Each dot corresponds to an observation in Block j in year t. We compute the investment ratio as total investment over total GDP in all countries in Block j, and GDP per capita as total GDP over total population in Block j. We use data from 1950-2017 for Block A and from 1960-2017 for Block B. Data Source: PWT9.1. The solid blue line corresponds to the fitted values of the regression $\frac{I_{At}}{Y_{At}} = \beta_0 + \beta_1 Year + \beta_2 Year^2 + \epsilon_{At}$. The dashed red line corresponds to the fitted values of the regression $\frac{I_{Bt}}{Y_{Bt}} = \beta_0 + \beta_1 Year + \beta_2 Year^2 + \epsilon_{Bt}$. The solid red line corresponds to the fitted values to the regression in A adjusted to match Block B's values in 1960.

from Block A to Block B in the mid- to late-1990s. Figure 2.5 plots private capital inflows (FDI and net portfolio investment) from Block A to Block B as a share of GDP (dark line, right axis) and the volume of direct and portfolio investment flows into Block B countries in Asia, Emerging Europe and Latin America (bars, left axis). As a consequence of the general liberalization of financial markets and the reduction in barriers to capital flow, Block B economies experienced a large increase in private foreign investment. In Section 6, we will show that this investment shifted the growth path of Block B economies, initially increasing the investment rate but requiring a higher level of manufacturing output in the long run to service its external debt.

The literature on structural transformation looks at shifts in supply and demand across sectors to explain the hump-shape in manufacturing and investment. Figure 2.6 plots the shares of agriculture, manufacturing and services in GDP for Block A between 1930 and 2017 period, and for Block B over the 1960 to 2017 period.

Figure 2.5: Private Capital inflows over GDP and flows of direct and portfolio investment into Block B



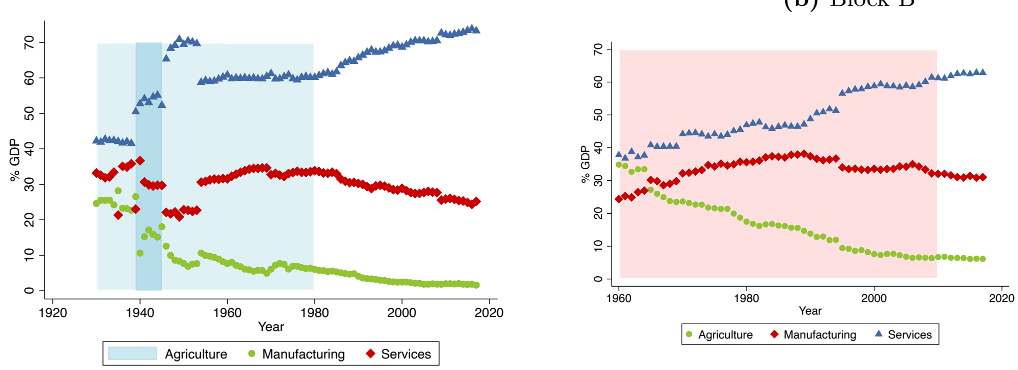
Note: Data Source WDI. Direct + Portfolio investment inflow is defined as net incurrence of direct investment and portfolio investment liabilities. Asia: India, Indonesia, South Korea, Malaysia, Taiwan, and Thailand. Europe: Greece, Ireland, Poland, Spain, Portugal and Turkey. Latin America and the Caribbean: Argentina, Brazil, Chile, Mexico.

Outside of the period around World War II, the figure captures the steady increase in the service sector as a share of GDP over time and the decline in agriculture. In Block A the manufacturing share rises until until 1980 and declines thereafter. In Block B the manufacturing share also rises and then declines slightly. Note that in each case the peak in manufacturing roughly corresponds with the peak in investment. It is instructive to compare Block's A and B at similar stages of development. Figure 2.7 plots the sectoral shares for both regions with date zero for Block A being 1930 and date zero for Block B going 1960. The sectoral shares in the two Blocks are almost identical at the beginning and the end of these two periods. Much of the deviation between the shares in the two blocks is associated with World War II and its aftermath. This similarity in experience is suggestive that the two regions are on a similar growth path, with Block B starting about three decades later than Block A.

Figure 2.6: Shares of agriculture, manufacturing and services in GDP

(a) Block A

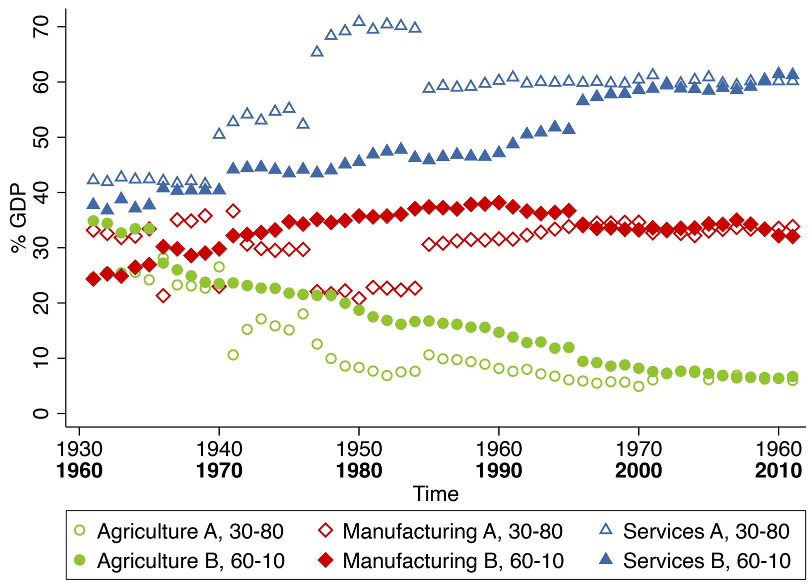
(b) Block B



Note: Data Source WDI for the period 1960-2017, and Madison Project Historical National Accounts for the period 1930-1960 for Block A. Agriculture includes ISIC 1-5, Manufacturing includes ISIC 10-45, and Services includes ISIC 50-99, Excluding mining and wholesale trade. We normalize the data such that the shares add to one.

To summarize, the four facts we want to explain are (i) investment rates exhibit a hump-shaped pattern, over time and with real income, (ii) investment peaks at a later date and at a lower level of real per capita income in Block B relative to

Figure 2.7: Comparing blocks: Sectoral Shares Block A 1930-1980, and Block B 1960-2010



Note: Data Source WDI. Agriculture includes ISIC 1-5, Manufacturing includes ISIC 10-45, and Services includes ISIC 50-99, Excluding mining and wholesale trade. Data for Block A corresponds to years 1960-1980, and data for Block B corresponds to years 1995-2017

Block A, (iii) both blocks experience structural transformation with a decline in the agricultural share roughly offset by an increases in the services share, and, like the hump in investment, this transformation occurs later in Block B relative to Block A, and (iv) Block B experiences a surge of private investment from Block A prior to its investment peak, which appears to be related to higher investment in Block B relative to what would have been predicted from the experience of Block A.

2.3 Model

We construct a model of growth and structural transformation that is consistent with the data both within and across countries, and captures the shifts in investment that occur with capital market integration. The global economy is comprised of two regional economies, corresponding to the two Blocks in the previous section.

Each regional economy has three sectors: agriculture, manufacturing, and services. Agents in each region choose consumption of the three goods, the allocation of capital and labor across the three sectors, and total capital investment to maximize the present value of utility. Structural transformation is generated in two ways: total factor productivity in each sector grows at a different rate and preferences are non-homothetic. In the latter we follow Echevarria (1997) and add additional terms to an otherwise homothetic utility function. We parameterize these terms so that the model convergences to a balanced growth path in the long run.

We attempt to keep the regions as similar as possible. In the end the two regions differ in four ways. To capture the fact that structural transformation and the peak of the investment hump in Block A occur earlier in time, we assume that Region A is further along in the development process in the sense that its productivity is higher and its preferences are closer to the long-run balanced growth path. Second, each region has a different initial capital stock. This allows us to match the data at the beginning of our sample in 1960. Third, while productivity growth at the sectoral level is identical in the two regions, manufacturing in Block B is relatively less productive than Block A. This will help the model match the fact that structural transformation and the peak of the investment hump in Block B occur at a lower level of per capita GDP. It will also help the model match differences in relative prices between the two blocks. Finally, the two regions differ in their size. Relative size will affect the way in which the impact of financial liberalization is distributed across the two Blocks. In all other aspects the two regions are identical.

We allow for interactions between the two regions. We assume the manufactured good is traded but agriculture and services are produced and consumed locally. This is consistent with the fact that most trade between Block A and Block B is in manufactured goods.[1] Because there is a single manufactured good in the model, all trade is intertemporal trade.[2] In the beginning of the sample, capital markets are closed so, in effect, each region functions as a closed economy. When capital markets in Block B liberalize, capital flows from Block A to Block B. The model incorporates adjustment costs in the accumulation of capital and in the accumulation of debt in order to slow the flow of capital between A and B.

We now present the model in detail.

2.3.1 The regional economies

Time is discrete and indexed by $t = \{0, 1, 2, \dots\}$. There are two regions labeled $i = \{A, B\}$ There are three sectors labeled $j \in \{a, m, s\}$ where a is agriculture, m is manufacturing and s is services. Each good is produced with capital and labor using a Cobb-Douglas production function. Capital is produced by the manufacturing sector. The sectoral production functions are:

$$\begin{aligned}
Y^i_{at} &= A^i \mu^{t-\bar{t}_i} (K^i_{at})^{\theta} (L^i_{at})^{1-\theta} \\
Y^i_{mt} &= B^i \lambda^{(t-\bar{t}_i)(1-\gamma)} (K^i_{mt})^{\gamma} (L^i_{mt})^{1-\gamma} \\
Y^i_{st} &= C^i \nu^{t-\bar{t}_i} (K^i_{st})^{\phi} (L^i_{st})^{1-\phi}
\end{aligned}$$

There are several things to note about these functions. First, they incorporate two of the main supply-side mechanisms for structural transformation. Productivity growth (μ, λ, ν) is sector specific as in Ngai and Pissarides (2007), and factor intensity $(\theta, \gamma, \varphi)$

[1] Appendix B.2 shows that 70% of trade between blocks A and B during 2000-2014 occurs in the manufacturing sector. Block A exports 1.8 % of GDP to Block B, and imports 1.4% in manufacturing, while Block B exports 5.8% of GDP to Block A and imports 7.4% in manufacturing.

[2] In this sense our model complements the work of Lewis et al. (2022). Their model focuses on shifts in comparative advantage and simplifies the intertemporal elements.

is sector specific as in Acemoglu and Guerrieri (2008). While these two sets of parameters differ across sectors, we assume that they are the same across the two regions. Second, the level of productivity may differ across regions. This is captured by the exponent $t - \bar{t}_i$. One can think of $\bar{t}_i$ as the date at which the region began the development process. A lower $\bar{t}_i$ means that the region has been growing for longer. Third, sectoral productivity may differ across regions. This is the role played by A^i, B^i, and C^i. This will allow us to match the fact that manufacturing is relatively less productive in Block B.

Given the total supply of capital and labor in the economy, firms in each sector employ capital and labor to maximize profits. As there are no state variables in the firm's problem. Profit maximization is static. Let P^i_{jt} denote the price of good j in region i at date t. We will take the manufacturing good to be the numeraire, $P^i_{mt} = 1$.[3] Let W^i_t and R^i_t denote the real wage and the real rental price of capital respectively. The firm's problem for agriculture becomes

$$\max_{K^i_{at}, L^i_{at}} P^i_{at} Y^i_{at} - W^i_t L^i_{at} - R^i_t K^i_{at}.$$

The problems for manufacturing and services take similar forms.

In each region there is a representative consumer that receives utility from the consumption of the three goods. The consumer maximizes the present discounted value of utility $\sum_t \beta^t U^i_t$ where β is the discount factor and the period utility U^i_t takes the form:

$$U^i_t = \sum_{j \in \{a,m,s\}} \alpha_j \ln(C^i_{jt}) - \epsilon^i_{jt} C^i_{jt}$$

[3]When the economies are closed $P^i_{mt} = 1$ is a normalization. When the economies are open, this is both a normalization and the result of free trade in manufactured goods and the absence of trade frictions.

The second term generates changes in the pattern of consumption over time, one of the drivers of sectoral change in the model. To capture the effect of preferences on structural transformation, we assume that the impact this second term declines over time as preferences adjust towards steady state:

$$\epsilon^i_{jt} = \rho_j \epsilon^i_{j,t-1}$$

As the ϵ^i_{jt} converge to zero, preferences converge to the familiar Cobb-Douglas form that is consistent with balanced growth. Whereas we model the deviation from Cobb-Douglas as a function of time. We think of this term as capturing non-homotheticicities in preferences that are important in the literature on sectoral change.[4] The consumer owns the capital stock. The consumer's budget constraint is

$$\sum_{j\in\{a,m,s\}} P^i_{jt}C^i_{jt}+K^i_{t+1}+D^i_t = W^i_t L^i_t + R^i_t K^i_t + (1-\delta)K^i_t + \frac{D^i_{t+1}}{1+r_t} - G(K^i_{t+1},K^i_t) - H(D^i_{t+1},D^i_t)$$

There are several things to note about this budget constraint. Investment is equal to $K^i_{t+1}-(1-\delta)K^i_t$ and has a price equal to one since it is in terms of the manufactured good. The function $G(K^i_{t+1},K^i_t)$ is a capital adjustment cost. There is a single international bond that pays one unit of the numeraire in the following period. D_t represents borrowing in this bond and r_t is the net interest rate. $H(D^i_{t+1},D^i_t)$ is a portfolio adjustment cost. Both G and H are in units of the manufacturing good.

The two adjustment costs take the following forms :

$$\begin{aligned} G(K^i_{t+1},K^i_t) &= \frac{\psi_1}{2}\frac{\left(K^i_{t+1}-K^i_t\right)^2}{K^i_t} \\ H(D^i_{t+1},D^i_t) &= \frac{\psi_2}{2}\frac{\left(D^i_{t+1}-D^i_t\right)^2}{\lambda^t} \end{aligned}$$

[4] Modelling the non-homothetic term as a function of time simplifies the computation of the steady state. ϵ^i_{jt} acts very much like a taste shock.

Note that the portfolio adjustment cost is symmetric so that the cost of increased borrowing is the same as the cost of increased lending. This symmetry implies that when the regions are open to intertemporal trade, the two regions will each face the same intertemporal marginal rate of transformation. Note also that when the economies are closed $D_t = 0$ and H and its derivatives are all equal to zero. In this case the international bond becomes a domestic bond in zero net supply.

r_t is the world interest rate (also in terms of the manufactured good). Note the interest rate r_t is related to the rental rate R_t by arbitrage

$$\frac{1 - H_{2,t+1}}{\frac{1}{1+r_t} + H_{1,t}} = \frac{R_{t+1} + (1-\delta) - G_{2,t+1}}{1 + G_{1,t}}.$$

Here $G_{k,t}$ represents the derivative of G with respect to its kth argument at date t, and $H_{k,t}$ has a similar interpretation. The left-hand side of the equation is the rate of return on the international bond where $\frac{1}{1+r_t} + H_{1,t}$ units of the manufacturing good are needed to purchase one unit of the bond which returns $1 - H_{2,t+1}$ units of the manufacturing good in the next period. The right-hand side is the rate of return on investment where $1 + G_{1,t}$ units of the manufacturing good are needed to secure one unit of investment which returns $R_{t+1} + (1-\delta) - G_{2,t+1}$ units of the manufacturing good the next period. Note that when the regions are in autarky the $H_{k,t}$ terms all become zero and the left-hand side simplifies to $1 + r_t$.

We assume that the two regions begin in autarky and open to trade at some date T. Prior to T, there is no trade in manufactured goods and holdings of the international bond are equal to zero. We assume that T is unanticipated.

Given this market structure, The market clearing conditions are the usual ones.

Since agriculture and services are non-traded,

$$C_{jt}^i = Y_{jt}^i \qquad j \in \{a, s\} \text{ and } i \in \{A, B\}$$

Market clearing for manufactured goods takes the form

$$C_{mt}^i + K_{t+1}^i - (1-\delta)K_t^i + G(K_{t+1}^i, K_t^i) = Y_{mt}^i \qquad i \in \{A, B\}$$

for $t < T$,

$$\sum_{i \in \{A,B\}} C_{mt}^i + K_{t+1}^i - (1-\delta)K_t^i + G(K_{t+1}^i, K_t^i) + H(D_{t+1}^i, D_t^i) = \sum_i Y_{mt}^i$$

thereafter. Note here that we assume that the adjustment costs are paid in terms of the manufactured good. For $t < T$, $D_t^i = 0$. Thereafter

$$D_t^A + D_t^B = 0$$

Finally factor markets clear

$$\begin{aligned} \sum_{j \in \{a,m,s\}} K_{jt}^i &= K_t^i \qquad i \in \{A, B\} \\ \sum_{j \in \{a,m,s\}} L_{jt}^i &= L^i \qquad i \in \{A, B\} \end{aligned}$$

Note here that we allow the size of the labor force to differ between the two blocks. We use this to adjust the relative size of the two regional economies. This merely scales the economies when they are closed. It affects the relative impact of capital flows when they open to intertemporal trade.

An equilibrium is a sequence of prices $\{r_t^A, r_t^B, P_{at}^A, P_{mt}^A, P_{at}^B, P_{mt}^B, W_t^A, R_t^A, W_t^B, R_t^B\}$, consumptions $\{C_{at}^A, C_{mt}^A, C_{st}^A, C_{at}^B, C_{mt}^B, C_{st}^B\}$, capital allocations $\{K_{at}^A, K_{mt}^A, K_{st}^A, K_{at}^B, K_{mt}^B, K_{st}^B\}$, and labor allocations $\{L_{at}^A, L_{mt}^A, L_{st}^A, L_{at}^B, L_{mt}^B, L_{st}^B\}$ such that firms and consumers maximize given prices and markets clear.

2.3.2 Solution

The model as written is non-stationary, with growing output and unstable consumption shares. The model can be transformed into a stationary model through the appropriate transformation. Specifically, as the impact of the non-homothetic preferences dissipates, the economy converges to a generalized balanced growth path in which the capital allocated to each sector grows at rate λ, so that all variables measured in terms of the manufactured good grow at rate λ, output and consumption of agricultural goods grow at rate $\lambda^{\theta}\mu$, and output and consumption of services grow at rate $\lambda^{\phi}\nu$. Along this balanced growth path prices of agricultural goods and services grow at rates $\lambda^{(\theta-1)}\mu$ and $\lambda^{(\phi-1)}\nu$ respectively. We use lower case letters to represent variables normalized by these growth rates. For example, $c^i_{at} = \frac{C^i_{at}}{\lambda^{\theta t}\mu^t}$, $c^i_{mt} = \frac{C^i_{mt}}{\lambda^t}$, and $c^i_{st} = \frac{C^i_{st}}{\lambda^{\phi t}\nu^t}$.[5] With this normalization the period utility functions become

$$U^i_t = \sum_{j\in\{a,m,s\}} \alpha_j \ln(c^i_{jt}) - \tilde{\epsilon}^i_{jt} c^i_{jt}.$$

Here $\tilde{\epsilon}^i_{at} = (\lambda^{\theta}\mu)^t \epsilon^i_{at}$ and $\tilde{\epsilon}^i_{mt}$ and $\tilde{\epsilon}^i_{st}$ are similarly related to ϵ^i_{mt} and ϵ^i_{st}. The budget constraint becomes

$$p^i_{at}c^i_{at}+c^i_{mt}+p^i_{st}c^i_{st}+k^i_{t+1}+\frac{\lambda d^i_{t+1}}{1+r_t} = w^i_t L^i_t - R^i_t k^i_t + (1-\delta)k^i_t - d^i_t - \frac{\psi_1}{2}\frac{(\lambda k^i_{t+1}-k^i_t)^2}{k^i_t} - \frac{\psi_2}{2}(\lambda d^i_{t+1}-d^i_t)^2$$

The production functions and market clearing conditions also become stationary.

Note that the consumption shares of the transformed economy are the same as the consumption shares of the original economy. For example, the consumption share of

[5]Other variables are defined similarly: $k^i_t = \frac{K^i_t}{\lambda^t}$, $k^i_{jt} = \frac{K^i_{jt}}{\lambda^t}$, $i^i_t = \frac{I_t}{\lambda^t} = \lambda k^i_{t+1} - (1-\delta)k^i_t$, $d^i_t = \frac{D^i_t}{\lambda^t}$, $w^i_t = \frac{W^i_t}{\lambda^t}$, $p^i_{at} = \lambda^{(\theta-1)t}\mu^t P^i_{at}$, $p^i_{st} = \lambda^{(\phi-1)t}\nu^t P^i_{st}$.

agricultural goods is

$$\frac{p^i_{at}c^i_{at}}{p^i_{at}c^i_{at}+c^i_{mt}+p^i_{st}c^i_{st}} = \frac{\lambda^{(\theta-1)t}\mu^t P^i_{at}\frac{C^i_{at}}{\lambda^{\theta t}\mu^t}}{\lambda^{(\theta-1)t}\mu^t P^i_{jt}\frac{C^i_{at}}{\lambda^{\theta t}\mu^t}+\frac{C^i_{mt}}{\lambda^t}+\lambda^{(\phi-1)t}\nu^t P^i_{st}\frac{C^i_{st}}{\lambda^{\phi t}\nu^t}} = \frac{P^i_{at}C^i_{at}}{P^i_{at}C^i_{at}+C^i_{mt}+P^i_{st}C^i_{st}}$$

This implies that the when the transformed economy is in steady state the consumption shares in the original economy are constant although prices and consumption continue to drift in opposite directions.

Our solution method consists in first solving the stationary version of the model and then recovering the results for the growing economy. In this sense, our solution is similar to Echevarria (1997). However, since we have an open economy, we require a shooting algorithm to find the long-run level of debt such that all of the restrictions in our model – including the transversality condition – are satisfied.

The algorithm proceeds as follows. We make a guess for the steady state trade balance of Block A and solve the perfect foresight model using this guess and the initial conditions for debt and the capital stocks in each block. Using this solution we verify if the transversality condition is satisfied. If the transversality condition is satisfied, our guess satisfies all the constraints and we have found a solution. If not, then we adjust our guess of the steady state trade balance appropriately. For example, if Block A has too much savings in the recovered equilibrium, we decrease our guess for the final trade balance position of Block A.

2.4 Calibration

In the model, the two blocks are essentially the same. The only differences are the initial capital stock (K^i_{1960}), the stage of the development process ($\bar{t}^i$), and the productivity parameters A^i, B^i, and C^i. Our strategy is to calibrate all common parameters to Block A. First we calibrate capital shares (θ, γ, φ), sectoral growth rates (μ, λ, μ), and depreciation (δ) to match the long run characteristics of Block A. Second, we calibrate the efficiency parameters (A^i,B^i,C^i) for each country to match the final output points in each block. Third, we calibrate preferences (α_j, ϵ_j, ρ_j) to match the initial and final points of the sectoral shares in Block A, and adjustment costs (ψ_1) to match the initial investment to GDP share to this same block. Fourth, we calibrate the portfolio adjustment costs (ψ_2) to match the capital inflows to Block B after integration. finally we calibrate the differences between the two Blocks. These include the relative size of the Block and its initial stage of development in 1960, in particular the efficiency parameters (A^i,B^i,C^i), and $\bar{t}_i$. Note that the evolution of the capital stock and structural change in Block B are all unmatched moments.

2.4.1 Long-run parameters

Production Functions

To calibrate the capital shares (θ, γ, φ), the growth rates of total factor productivity in agriculture and services (μ, ν), and labor augmenting total factor productivity in manufacturing λ, we use data from the WIOD from 2000 to 2014 for countries in Block A in local currency units. In particular we use data on sectoral wages, total hours, number of workers, and total output per sector and year in local currency units. We define our three sectors aggregating SIC sub sectors as follows: agriculture in the model corresponds to agriculture and mining in SIC 01-14; manufacturing includes manufacturing and construction SIC 15-39; and services includes SIC 40-97.

We define the capital share as one minus the labor share, averaged across countries and over time. Table B.2 in the Appendix shows the summary statistics by country in Block A. To aggregate, we first take the average per year over all countries in the block and then we average over all years. Table 2.2 shows the summary statistics for these parameters. According to the data agriculture is the most capital intensive sector and manufacturing is the least capital intensive sector.

Table 2.2: Summary Statistics: Capital Shares

		Mean	**Std. Dev**	**Min**	**Max**
Agriculture	θ	0.54	0.21	0.14	0.87
Manufacturing	γ	0.36	0.06	0.23	0.48
Services	φ	0.39	0.04	0.34	0.46

Note: Agriculture and Mining SIC 01-14; Manufacturing and Construction SIC 15-39; Services SIC 40-97.

To calculate the growth rates of total factor productivity in agriculture and services (μ, ν), and the growth rate of labor augmenting TFP in manufacturing λ, we use data on output, capital, labor in each sector of each country in Block A together with the estimated capital shares to calculate TFP for each sector of each country in years 2000 and 2014. We use these estimates of TFP to compute TFP growth rates by country and sector, and then average across countries in the Block.[6] Table B.3 in the Appendix shows the summary statistics per country in Block A between 2000-2014. Then we define $\mu = \exp(g_{jA} - (1-\theta)n)$ as the growth rate in agriculture, $\nu = \exp(g_{jC} - (1-\varphi)n)$ as the growth rate in services, and $\lambda = \exp(\frac{g_M}{\gamma} - n)$ as the growth rate in manufacturing. Where n is average population growth rate in the US between 1960 and 2017, which is equal to $n = 0.98\%$. [7]

Table 2.3 summarizes these results, with the calibrated parameters corresponding to the first column. Productivity growth is highest in manufacturing. Productivity growth is roughly equal in agriculture and services.[8]

Note that factor intensity differs across sectors, but productivity growth is very

[6] We choose 2000 and 2014 because those are the years for which WIOD provides data on capital and employment

Table 2.3: Summary Statistics: Total Factor Productivity Growth

		Mean	Std. Dev	Min	Max
Agriculture	μ	1.0028	0.0462	0.9334	1.1017
Manufacturing	λ	1.0212	0.0278	0.9625	1.0714
Services	ν	1.0049	0.0160	0.9573	1.0235

Note: Agriculture and Mining SIC 01-14; Manufacturing and Construction SIC 15-39; "Services SIC 40-97.

similar across sectors. Hence factor intensity will play a larger role in generating structural transformation in our model (Acemoglu and Guerrieri (2008)), than will differences in productivity growth (Ngai and Pissarides (2007)).

Depreciation and Discount Factor

To calibrate the depreciation rate, δ, we use the annual depreciation rate from Penn World Table 9.1 from 1960 to 2017. Following the same pattern of aggregation, we first average depreciation rate per year over all countries in Block A, and then we average over all years. Table 2.4 summarizes these results.

To calibrate the discount factor, β, we set the steady state interest rate equal to 4.8%. This rate corresponds to the average 1-year Treasury constant maturity rate between 1953 to 2017.[9] We use the debt Euler equation to derive β. This condition implies a discount factor $\beta = 0.9671$.[10]

2.4.2 Preferences and Adjustment Costs

We calibrate the utility parameters ($\alpha_j, \epsilon_j^A, \rho_j$ for $j = \{a, m, s\}$) and the investment adjustment costs (ψ_1) to match the sectoral output shares in 1991, 1960 and 1930 in

across sectors.

[7] The model results are not qualitatively sensitive to the population growth rate or the aggregation method.

[8] Recall, that λ is labor augmenting, while μ and ν are not. TFP growth in manufacturing is roughly $1.0212^{0.64} = 1.0135$.

[9] Source FRED

[10] In steady state the debt Euler equation is:

$$\lambda \left[\frac{1}{1+r} - \psi_2(\lambda - 1) \right] = \beta \left[1 - \psi_2(\lambda - 1)\lambda \right]$$

Table 2.4: Summary Statistics: Depreciation Rate

		Mean	Std. Dev	Min	Max
Depreciation (%)	δ	3.7	0.2	3.5	4.2

Note: Using data from Penn World Table 9.1 the table shows summary statistics for the depreciation rate of Block A between 1960-2017. We compute Block's A depreciation rate as the average depreciation rate by year of all countries in Block A.

the data for Block A, as well as the investment share in 1960. To calibrate α_j we use sectorial output shares from WDI[11] for 1991, and investment share from PWT 9.1. Recall that the non-homothetic term declines, and preferences converge to Cobb-Douglas preferences. We assume that Block A was in steady-state in 1991 before the market integration. Since in our model production of manufacturing includes investment and capital adjustment costs, the relationship between the production shares in the data and the steady-state consumption in the model is defined as follows:

$$\alpha_a = \frac{Y_a}{1 - IY} = 0.0544$$
$$\alpha_m = \frac{Y_m - IY}{1 - IY} = 0.0677$$
$$\alpha_s = \frac{Y_s}{1 - IY} = 0.8779$$

where Y_j for $j = \{a, m, s\}$ are the production shares in the data, and IY is the investment share in the data. Note the large service sector share reflects the importance of services near the end of the sample.

To calibrate ϵ^A_{j0}, ρ_j, and ψ_1 we use an iterative process to match the model with the data production shares in 1930 and 1960, and the investment share in 1960. We first guess some values for ϵ^A_{j0}, ρ_j, and ψ and we solve for the closed economy model

[11] Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Manufacturing corresponds to ISIC divisions 10-45, including mining, and services correspond to ISIC divisions 50-99.

between 1930 to 1960 for Block A. Then we compute the difference between the model and the data consumption shares in 1930 and 1960. ϵ_j governs the curvature of the curve, and allows to match the initial year, while ρ_j governs the persistence and allow us to match 1960's shares. ψ_1 governs the initial level of the investment share.[12] We iterate the model over a grid of values until the rates match by first increasing ϵ_a and ϵ_m and then adjusting ϵ_s. Once we fix the initial point we adjust the persistence level until we match 1960's values. Finally, we adjust ψ_1 to match the investment share in 1960. Figure B.3 in the appendix shows the simulated path of the non-homothetic term per sector and block.

Using the same iterative process, we calibrate the portfolio adjustment cost parameter (ψ_2) to match the area under the capital inflows to Block B between 1991 and 2017.

2.4.3 Differences between Blocks

Finally, we calibrate the parameters that differ between Blocks A and B. First, we initialize the development process. This involves both the parameter $\bar{t}_i$ and the initial capital stocks. It is important to notice that according to our model, all economies are following the same development process, and differences in GDP can be interpreted as the economies being at different points on this path. In this sense, we solve for an arbitrary closed economy with an initial capital stock close to zero[13], and define that each Block is in the period that minimizes the distance between the real GDP per capita in 1960 and the GDP implied by this path. We find that Block A in 1960 was on its 40th year of the development path, while Block B was in the 20th year of the

[12]Recall the the hump-shaped is explained by the non-homothetic term with the different sectoral growth rates. We do not match the path, only the initial point.

[13]The minimum possible capital stock to obtain a solution for the model corresponds to \$10 US in PPP 2011

development path, and use as the initial capital stock the implied level by $\bar{t}_A = 1920$ and $\bar{t}_B = 1940$

Second, we calibrate the efficiency parameters $\{A^i, B^i, C^i\}$ to match the output levels on each block in 2017. To do so, we use the parameters of the model, data on GDP per capita in 2017, and data on relative prices of consumption in 2017 on each block to solve for the steady state of the stationary closed economy. We use data from the ICP in 2017 on sectoral relative prices and real GDP *per capita* in PPP for Block A from PWT 9.1. We compute relative prices in agriculture and services as the deflator per sector, that is nominal expenditure to real expenditure, to the corresponding price in manufacturing. Following Echevarria (1997) we classify expenditure in three sectors. First, agriculture (Cat. 03-04) includes food and non-alcoholic beverages, alcoholic beverages, tobacco, non-alcoholic beverages, and alcoholic beverages, tobacco and narcotics; manufacturing (Cat 05-07) includes clothing and footwear, actual housing, water, electricity, gas and other fuels, furnishings, household equipment and routine household maintenance, purchase of vehicles, net purchases abroad, and collective consumption expenditure by government; finally, services (Cat. 08-14) include health, transport, communication, recreation and culture, education, restaurants and hotels, miscellaneous goods and services, and transport. Table 2.5 shows relative prices and GDP per capita in year 2017. P_1, P_2, and P_3 correspond to the deflator in the data, while p_1 and p_3 are the relative prices.

Finally, we calibrate ϵ^B_{j0} to capture the difference in the structural transformation process. We set ϵ^B_{j1960} as the one Block A had in 1930 as follows:

$$\epsilon^A_{1930-\bar{t}_{A,j}} = \epsilon^B_{1960-\bar{t}_{A,j}}$$

Table 2.5: GDP per capita and Relative Prices in 2017

	GDP	P_1	P_2	P_3	p_1	p_3
Block A	\$48,465	0.94	1.01	1.09	0.94	0.98
Block B	\$12,094	0.77	1.12	1.09	0.70	0.99

Note: Agriculture (Cat. 03-04) includes food and non-alcoholic beverages, alcoholic beverages, tobacco, non-alcoholic beverages, and alcoholic beverages, tobacco and narcotics; Manufacturing (Cat 05-07) includes clothing and footwear, actual housing, water, electricity, gas and other fuels, furnishings, household equipment and routine household maintenance, purchase of vehicles, net purchases abroad, and collective consumption expenditure by government; Services (Cat. 08-14) include health, transport, communication, recreation and culture, education, restaurants and hotels, miscellaneous goods and services, and transport.

Recall that $\bar{t}_{A,j} = 1920$ and $\bar{t}_{B,j} = 1940$. Table 2.6 presents all the parameters in the calibrated model.

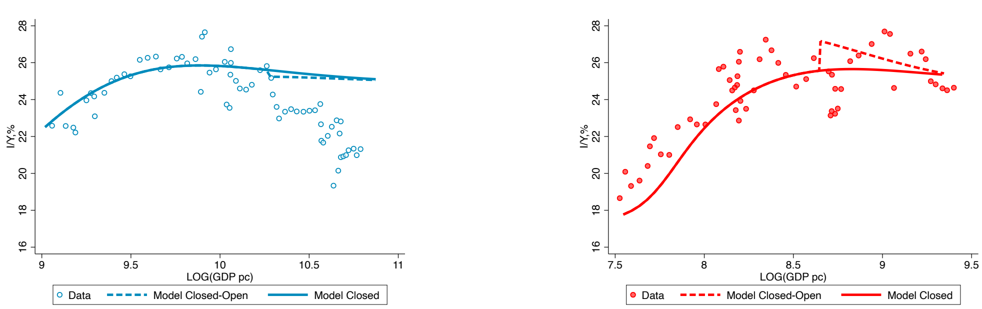
Table 2.6: Parameters

Preferences								
$\alpha_1 = 0.05$	$\alpha_2 = 0.06$	$\alpha_3 = 0.87$	$\epsilon^A_{1,0} = 11.2$	$\epsilon^A_{2,0} = 22$	$\epsilon^A_{3,0} = -0.6$	$\rho_1 = 0.91$	$\rho_2 = 0.88$	$\rho_3 = 0.96$
Production								
$A^A = 1.34$	$B^A = 0.48$	$C^A = 1.19$	$A^B = 1.21$	$B^B = 0.24$	$C^B = 0.64$	$\mu = 1.002$	$\lambda = 1.02$	$\nu = 1.004$
$\theta = 0.49$	$\gamma = 0.37$	$\phi = 0.40$						
Other								
$\beta = 0.97$	$\delta = 0.04$	$\psi = 5.8$	$\psi_2 = 1.05$	$t_{1A} = 1920$	$t_{1B} = 1940$			

2.5 Comparing the Model to the Data

Figure 2.8: The simulated paths of the investment rate relative to real per capita GDP for both Blocks A and B

(a) Block A **(b)** Block B



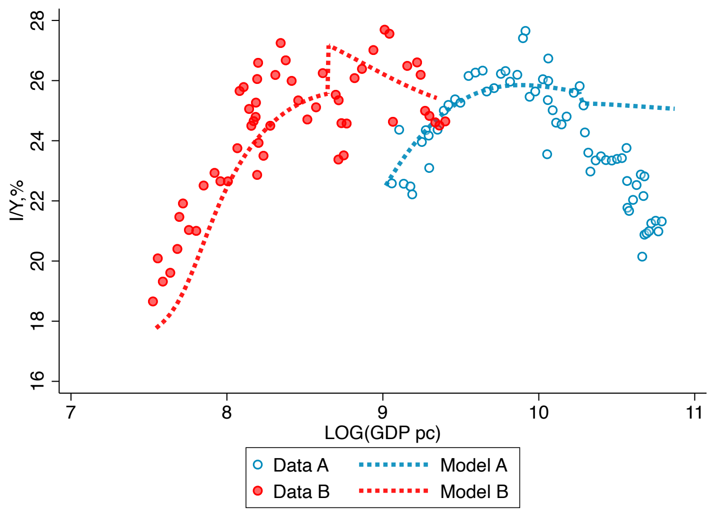
Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The solid line corresponds to the simulated results of the closed economy, and the dashed line corresponds to the open economy opening in 1991.

Given the calibrated parameters, we simulate the model assuming financial markets open in 1991. Prior to 1991, both regions are effectively closed. After 1991, they engage in intertemporal trade. The opening of financial markets is unanticipated. We start by comparing the simulated paths for the investment rate as a function of real per capita income in the data and in the model (Figure 2.8). The dots in the figure are data and correspond to the dots in Figure 2.3. The solid line in the figure shows the path of investment for each block under the assumption that both blocks remain closed through the full sample. The light dotted line shows the perturbation to investment in both regions when the economies open to capital flows.

There are several points to emphasize in the figure. First, the investment rates produced by the model exhibit the hump shape in the data. This was fact 1. Second, the investment rate peaks at a lower level of per capita income in Block A than in Block B. This was fact 2. The final observation is that when capital market liberalization occurs, the investment rate drops in Block A and increases in Block B. The increase in B is larger because it is expressed as a share of GDP, which is lower in Block B. In both cases the open-economy path fits the data somewhat better than the closed-economy path. The improvement in fit is even more evident in Figure 2.9 where the two investment curves are plotted together. Block B peaks at a lower level of per capita income and openness accelerates the increase in investment. Where the model misses most badly is in matching the large decline in investment among in Block A near the end of the sample.

Recall that the model is calibrated to match Block A prior to opening. The only parameters chosen to match Block B are the initial capital stock, the efficiency parameters, and the date at which development begins. In addition, the model abstracts from all financial crises, including the debt crises of the 1980's, the Asian Crisis and the Great Recession in 2008. In spite of all this, the model fits the evolution of investment in Block B remarkably well.

Figure 2.9: The simulated paths of the investment rate relative to real per capita GDP for both Blocks A and B



Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The dashed line corresponds to the simulated results of the model opening in 1991.

To understand what features of the model determine the hump-shape on investment Figures 2.10a and 2.10b compare the simulated paths of the investment share between the model and data using different specifications. Panel (a) shows the baseline model. Panel (b) eliminates differences across sectoral growth rates by setting all the sectoral rates to 1.01. Panel (c) eliminates differences in the labor shares across

Figure 2.10a: Determinants of the hump shape: Block A

(a) Baseline **(b)** Growth rates **(c)** Labor shares **(d)** Efficiency **(e)** Preferences

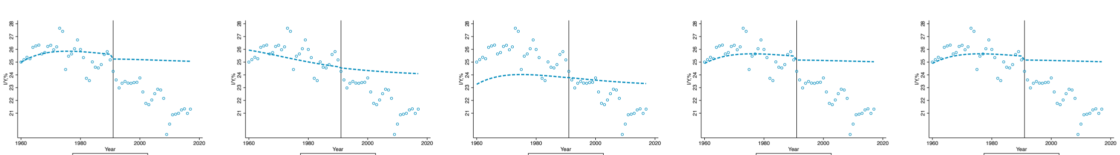
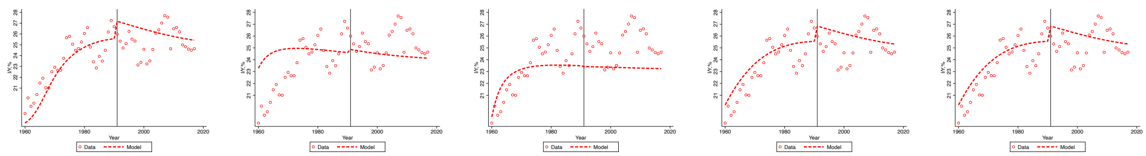


Figure 2.10b: Determinants of the hump shape: Block B

(a) Baseline **(b)** Growth rates **(c)** Labor shares **(d)** Efficiency **(e)** Preferences



Note: Panel (a) compares the simulated path of the investment share to GDP versus of the baseline model. Panel (b) uses the same growth rate across sectors and regions. We set $\lambda = \mu = \nu = 1.01$. Panel (c) the same labor share across sectors and regions $\theta = \gamma = \varphi = 0.38$. Panel (d) uses the same efficiency parameters across sectors by region: $A^A = B^A = C^A = 0.48$, and $A^B = B^B = C^B = 0.24$. Panel (d) uses Cobb-Douglas preferences. We set $\epsilon^i_{j,0} = 0$ and $\rho_j = 0$.

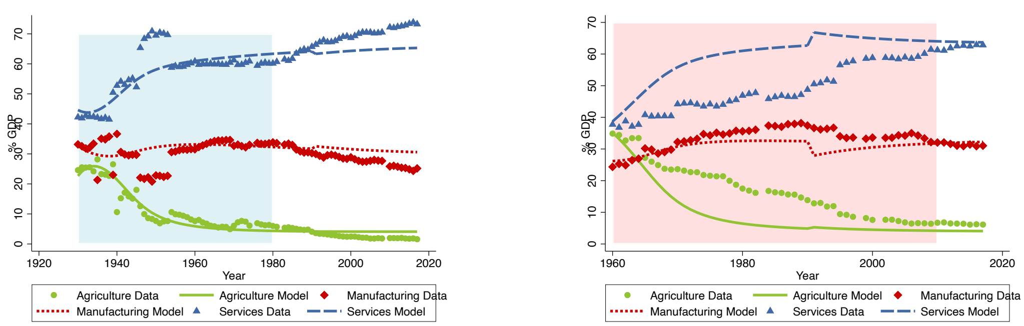
sectors and regions by setting all labor shares equal to the baseline value of the manufacturing sectors, 0.38. Panel (d) eliminates differences in the efficiency parameters across sectors, but keeping the difference between regions. We set the efficiency parameters equal to the baseline efficiency parameter in manufacturing per block, 0.48 and 0.24 correspondingly. Panel (e) eliminates the non-homothetic term by setting $\epsilon^i_{j,0}$ and ρ_j to be equal to zero. The features that are most important in matching the investment path are the differential sectoral growth rates and the differential factor shares. Non-homothetic preferences and levels of sectoral productivity have little effect.

The model also produces time paths for production by sector that can be compared to data. Figure 2.11 provides this comparison for both Blocks A and B. The model (dotted lines) generates paths that are roughly consistent with the data - the general decline in agriculture and the increase in services - though the fit is better for Block A than for Block B. Recall that the model is calibrated to match Block A as closely as possible. Only the date at which development begins is chosen to match Block B. Our third fact states that structural transformation and investment in Block B from 1960 to 2010 is comparable to Block A from 1930 to 1980. Figure 2.12 repeats this exercise with the simulated data. The sectoral shares from the shaded areas of Figure 2.12 are remarkably similar.

In contrast to the features of the model that determine the hump-shape on investment, the key parameters that explain the structural transformation path are those in the non-homothetic term of the preferences and the efficiency parameters. Figures B.6a and B.6b in the appendix repeat the exercise of eliminating one sectoral differences.

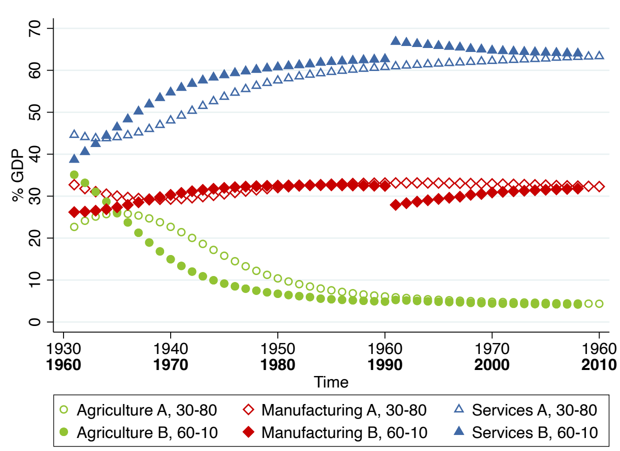
Figure 2.11: The simulated paths of the production by sector for both Blocks A and B

(a) Block A **(b)** Block B



Note: Data Source WDI. Agriculture includes ISIC 1-5, Manufacturing includes ISIC 10-45, and Services includes ISIC 50-99.Excluding mining and wholesale trade.

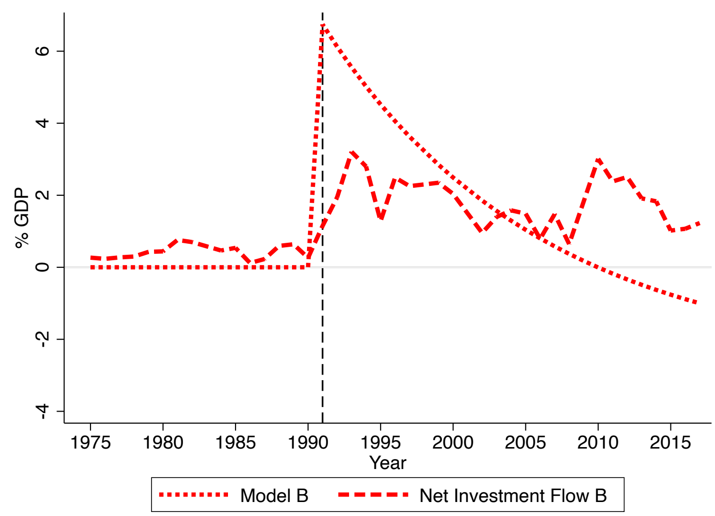
Figure 2.12: The simulated paths of the production by sector for both Blocks A and B



Note: Data Source WDI. Agriculture includes ISIC 1-5, Manufacturing includes ISIC 10-45, and Services includes ISIC 50-99, Excluding mining and wholesale trade.

Our fourth fact is that there was a surge in capital flows beginning around 1991. Figure 2.13 shows private capital flows from Block A to Block B in the model and the data. The initial date of liberalization is assumed to be 1991. The volume of capital flow shown in the figure is endogenously generated by the model. The surge in capital flows peaks at around 8 percent of Block B GDP, higher than in the data. However, it drops off quickly. The volume of capital flow from 1991-2005 in the model is 48.4% of GDP while it is 32.4% in the data.

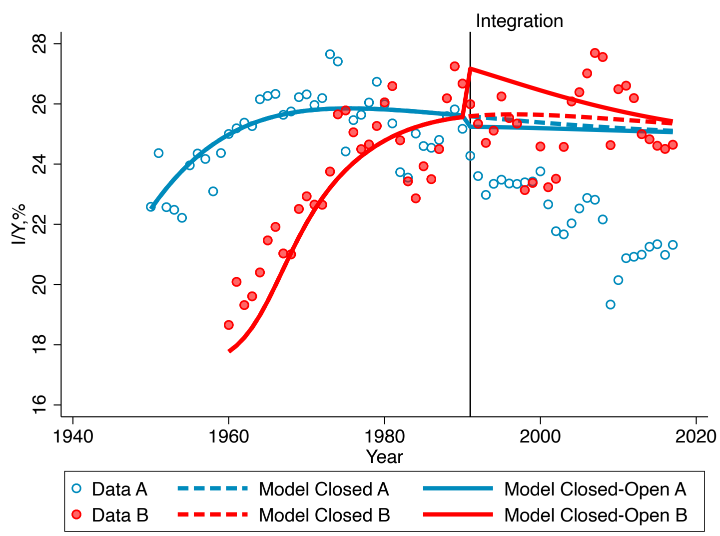
Figure 2.13: The simulated paths of the private capital flows from Block A to Block B



Note: Data Source WDI. Total Capital inflow is defined as net incurrence of liabilities excluding derivatives. Direct + Portfolio investment inflow is defined as net incurrence of direct investment and portfolio investment liabilities.

The surge in capital flows causes both investment and consumption to rise in Block B and fall in Block A. Figure 2.14 plots each investment curve (model and data) relative to time. The vertical line shows the date of capital market liberalization. At that point, the two investment paths diverge, causing the investment rate to rise in Block B and fall in Block A. The investment rate in Block A then flattens relative to the closed-economy path. Because Block B has borrowed from Block A and must pay interest in terms of the traded manufacturing good, in the very long run B's investment rate is slightly above where it would have been as a closed economy, and in A it is slightly lower. (see Figure B.4 in the Appendix.)

Figure 2.14: The simulated paths of the investment rate relative to time for both Blocks A and B

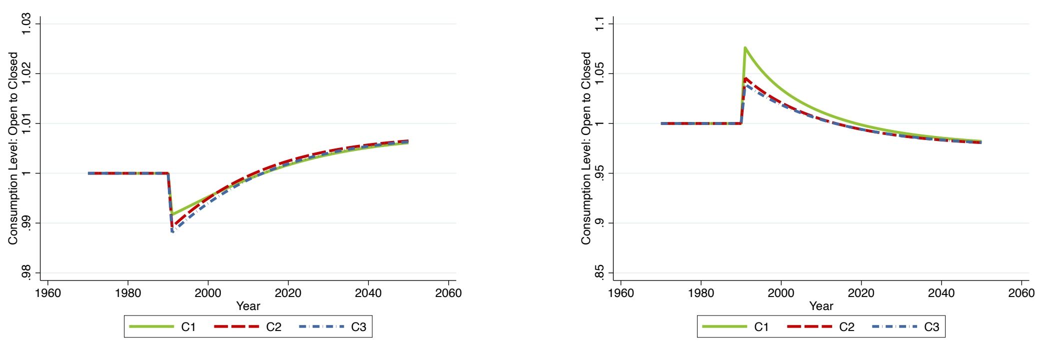


Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The solid line corresponds to the simulated results of the closed economy, and the dashed line corresponds to the open economy opening in 1991.

The rise in investment in Block B raises output and consumption. Figure 2.15 shows the impact of capital market liberalization on consumption of each of the three goods in Block A and Block B. The figure plots the time path of consumption relative to the path consumption would have followed if the economy had remain closed. Block B consumption rises on impact. Consumption of the agriculture increases the most, while services increase the least. There are two effects that alter the composition of consumption. First, the rise in investment increases the supply of capital and drives down the price of capital intensive goods such as agriculture. Second, capital market liberalization accelerates Block B along the development path (income effect) through non-homothetic preferences. This would increase consumption of services and manufacturing relative to agriculture. By 1991, the non-homothetic term is dominated by the prices of investment goods, so consumption of agriculture goods rises most. Note that overall consumption rises in the short run, but falls in the long run. In the long run Block B must pay for the capital it borrows in the short run.

Figure 2.15: The impact of capital market liberalization on consumption of each of the three goods in Block A and Block B

(a) Block A **(b)** Block B

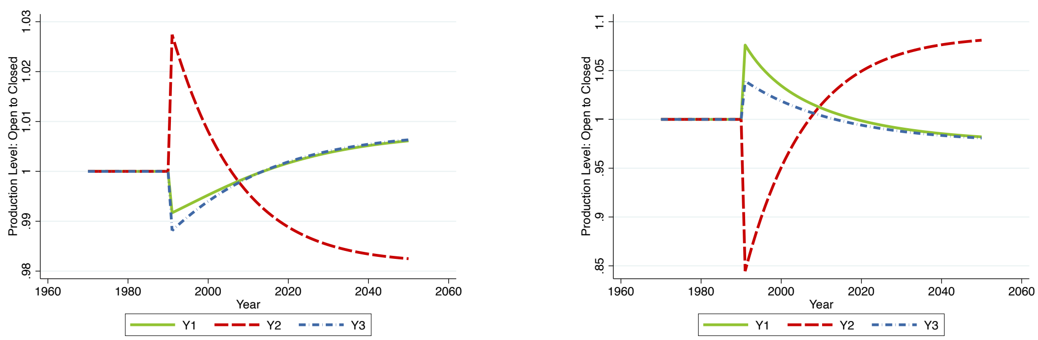


The response of consumption in Block A is the mirror image of the response of Block B. In the short run, consumption falls in Block A as the Block attempts to take advantage of profitable investment opportunities in Block B. In the long run Block A is able use its accumulated wealth to consume more than it would have had the economy remained closed.

We see the effects of financial liberalization on sectoral production in Figure 2.16. In Block A, the desire to export capital causes production to shift towards manufacturing. This shift comes mainly at the expense of services, as agricultural demand remains relatively strong. The response of Block B is the mirror image.

Figure 2.16: The impact of capital market liberalization on production of each of the three goods in Block A and Block B

(a) Block A **(b)** Block B



2.6 Welfare

In this section we use our model to evaluate the welfare effects of capital market liberalization. Who gains from liberalization? How does the timing of reform affect these gains? Not surprisingly we find that the welfare gains are larger if the two economies integrate earlier. We find that Block B gains more than Block A, and that Block B's gains are more sensitive to the timing of liberalization.

Evaluating the welfare effects of a policy change in a multi-good setting is not as straightforward as it is in a single-good economy. There is no natural numeraire good in a multi-good setting. Microeconomic theory has focused on two different measures of the welfare impact of a change in policy. These two measures agree on the sign of the welfare change, but, since they use different prices, they can differ in magnitude. The first is the *compensating variation*. The compensating variation takes as its starting point the post-reform equilibrium and the post-reform prices. It asks, "How much and in what direction must the present value of income change in order for agents to experience the pre-reform present-value utility at these post-reform prices?" In this sense, it reflects the compensation that would make agents living in the post-reform world indifferent to the reform (ignoring the general equilibrium feedback that actual compensation would naturally bring on). The *equivalent variation*, on the other hand, begins with the pre-reform equilibrium and the pre-reform prices, and asks "How much and in what direction must the present value of income change in order for agents to experience the post-reform present-value utility at the pre-reform prices?" The equivalent variation measures the wealth change that is equivalent to the policy reform from the pre-reform perspective.

Let $E_t(V_t, P_t)$ denote the expenditure in date t necessary to reach present value utility $V_t = \sum_t^\infty \beta^t U_t$ given a price vector P_t. Note that P_t is a vector of the date-t prices of all goods in all periods $s \geq t$. We can write the compensating variation of a reform at date t as,

$$CV_t = E_t(V_t^{open}, P_t^{open}) - E_t(V_t^{closed}, P_t^{open})$$

Here V_t^{open} is the present value of utility if capital markets are opened in period t and V_t^{closed} is the present value of utility of capital markets remain closed forever. P_t^{open} is the price vector if capital markets are open. As noted above, the compensating variation uses post-reform prices to transform the change in utility into a change in expenditure. If $CV_t > 0$, the reform raises welfare. Similarly we can write the equivalent variation of a reform at date t as,

$$EV_t = E_t(V_t^{open}, P_t^{closed}) - E_t(V_t^{closed}, P_t^{closed})$$

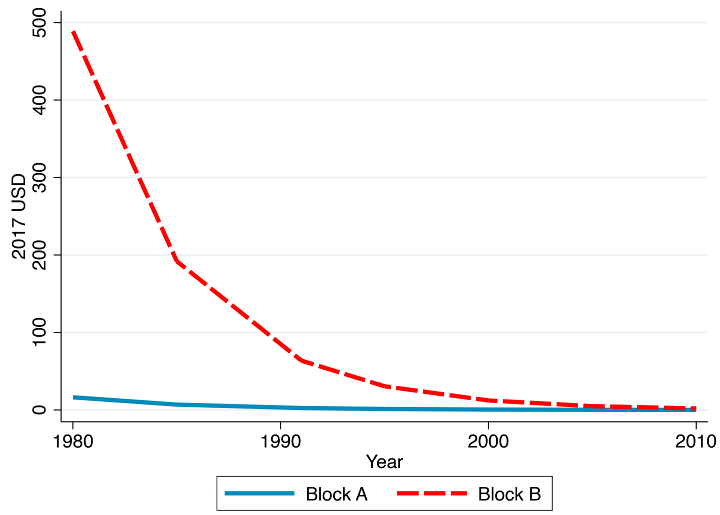
where the only change is that the equivalent variation uses P_t^{closed}, the price vector in the case that capital markets remain closed, to transform the change in utility in to a change in expenditure. Given that expenditure E_t is monotonically increasing in utility V_t, the compensating variation CV_t and equivalent variation EV_t are either both positive or both negative.

Using our model to calculate these quantities, we find liberalization in 1991 was welfare improving for both blocks, but that Block B gained more from liberalization than Block A.[14] The compensating variation to liberalization in 1991 is 0.005% of GDP for Block A and 0.286% of GDP for Block B. The equivalent variations are 0.005% for Block A and 0.268% for Block B. The per capita gains implied by the compensating variation in terms of 2017 US dollars are \$2.5 in Block A and \$65.7 in Block B.

We can also use the model to investigate the welfare effect of varying the date of liberalization. Figure 2.17 graphs the compensating variation as a function of the date of liberalization. One complication is that CV_t is calculated in terms of the numeraire at date t. In order to make all of the quantities comparable, we used the closed economy interest rate to transform all expenditure into 2017 dollars. Here we find that the gains to Block A are relatively insensitive to the data of liberalization, whereas Block B has a clear preference for liberalizing earlier.

[14] Interestingly, which region gains is somewhat sensitive to how we allocate countries to Blocks A and B. For example, if Greece, Ireland, Portugal and Spain are assigned to Block A, then Block A gains slightly more from liberalization than does Block B.

Figure 2.17: The impact of capital market liberalization on welfare in Block A and Block B



Note: The x-axis shows different opening dates. The y-axis shows the per capita CV in 2017 US dollars. We compute the CV as the present discounted value of expenditure under the open economy since the opening date, minus the presented discounted value of the expenditure required to keep the closed economy utility with the new prices.

2.7 China's Integration

Our two-country model includes the North and the South but excludes China, which is becoming an increasing force in world markets. It is natural to ask how the investment patterns would change if we were to include China in the model. To date, China remains largely closed to private capital flows. It is very difficult for foreigners to invest in China and own Chinese companies. The question then becomes, "What would happen if China liberalized its capital markets?"

To answer this question, we consider a simple experiment. Rather than solve a three country model with three sectors, we model China as a new exogenous investment opportunity. In our experiment, we assume that China liberalizes to asset trade with Blocks A and B in 2017 (which is the end of our sample). We assume that both Blocks A and B can trade with China at an exogenous interest rate that mimics the path of the world interest rate after the integration of Blocks A and B. Otherwise the

Table 2.7: The impact of capital market liberalization with China on welfare in Block A and Block B

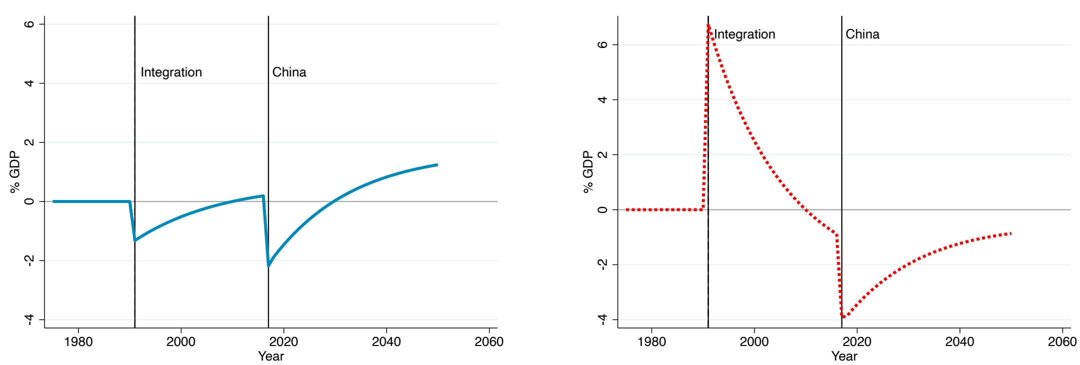
	CV (%GDP)	CV p.c.	EV (%GDP)	EV p.c
		Liberalization		
Block A	0.005%	$2.5	0.005%	$2.5
Block B	0.286%	$63.7	0.268%	$59.5
		Integration with China		
Block A	0.009%	$ 4.5	0.009%	$ 4.7
Block B	-0.768%	$-170.95	-0.802%	$-178.47

Note: We compute the CV as $PV\big((E(U_{\text{Open}}, P_{\text{Open}})\big) - PV\big(E(U_{\text{Closed}}, P_{\text{Open}})\big)$. We compute the EV as $PV\big((E(U_{\text{Open}}, P_{\text{Closed}})\big) - PV\big(E(U_{\text{Closed}}, P_{\text{Closed}})\big)$. All computations are in 2017 US dollars. CV (%GDP) and EV (%GDP) use GDP of the baseline open economy in 2017.

calibration of the model is the same. In effect, Blocks A and B are modeled as small open economies, facing an exogenously higher Chinese interest rate. This experiment should give a qualitative indication of the impact of Chinese liberalization.

Figure 2.18: The simulated paths of Capital inflows after integrating with China

(a) Block A **(b)** Block B



Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The dark dotted line corresponds to the simulated results of the model opening in after integrating with China. The light dashed line corresponds to the base-line model.

Table 2.7 shows the welfare impact of Chinese liberalization. Block A gains after the integration, but Block B loses. To get some idea of why Block A gains more than Block B. Figures 2.18a and 2.18b illustrate the path of capital flows for two integration dates. We see that capital flows from Block A to Block B when these two regions integrate in 1991, but capital flows from both blocks towards China when

China integrates. Figure 2.19a shows that saving rises in both blocks and investment falls.

Figure 2.19a: The simulated paths of Savings and Investment after integrating with China: Block A

(a) Savings **(b)** Investment

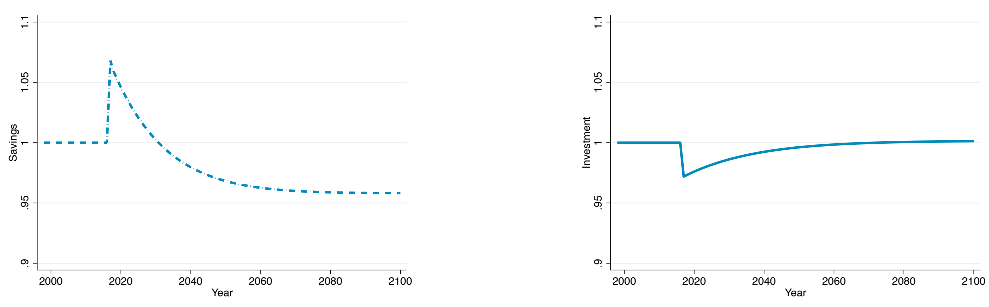
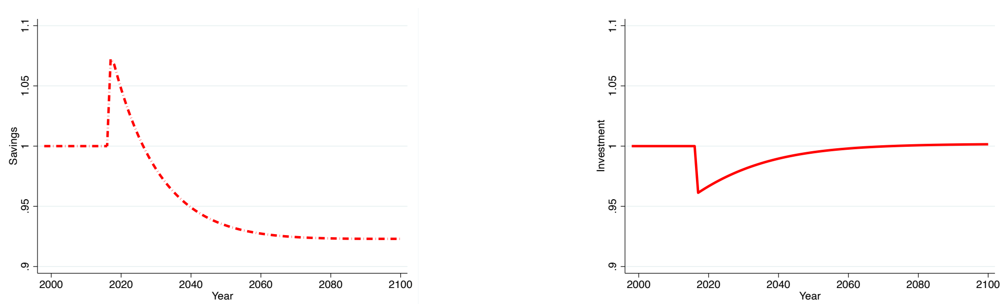


Figure 2.19b: The simulated paths of Savings and Investment after integrating with China: Block B

(a) Savings **(b)** Investment

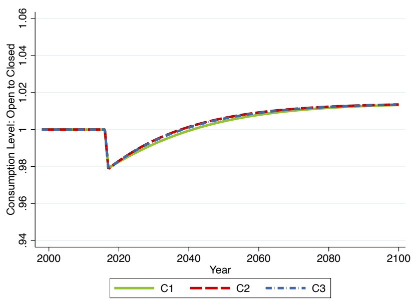


Note: Each dot corresponds to an observation in Block j in year t.The x-axis shows years and the y-axis is the ratio of the counter-factual model to the vase line model. Data Source: PWT9.1. The dark dotted line corresponds to the simulated results of the model opening in after integrating with China. The light dashed line corresponds to the base-line model.

The picture that emerges is that China's liberalization presents the world with a new investment opportunity and raises the world interest rate and the marginal product of capital. This raises income in both blocks and causes capital to shift toward China. There is an additional effect of integration, however. Block A is a creditor at the time of liberalization, whereas Block B is a debtor. The rise in interest rates therefore further raises the wealth of Block A, whereas it represents a capital loss in Block B.

Figure 2.20: The simulated paths of Consumption and Production after integrating with China: Block A

(a) Consumption



(b) Production

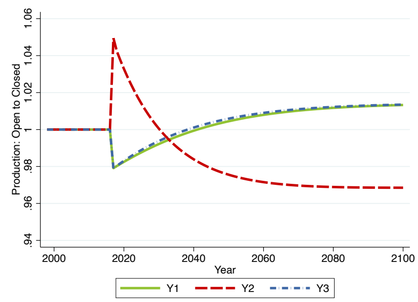
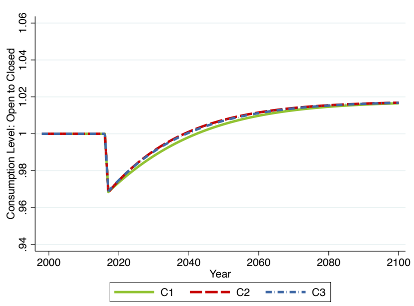
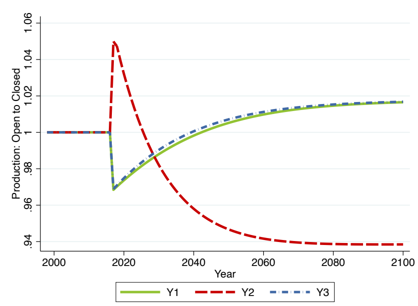


Figure 2.21: The simulated paths of Consumption and Production after integrating with China: Block B

(a) Consumption



(b) Production



Note: Each line corresponds to the co Block j in year t.The x-axis shows years and the y-axis is the ratio of the counter-factual model to the vase line model. The dark dotted line corresponds to the simulated results of the model opening in after integrating with China. The light dashed line corresponds to the base-line model.

The opening of China has interesting implications for the allocation of consumption and production across sectors as shown in figures 2.20 and 2.21. The increased investment opportunities lead to a surge in manufacturing production in both Blocks A and B. Consumption in both regions falls in the short run and increases in the long-run.

2.8 Conclusions

In this paper, we develop a two-region model of the world economy that successfully mimics the dynamics of investment and sectoral change in advanced economies as well as emerging markets. The investment rate exhibits a "hump shape," increasing at early stages of economic growth and then declining at later stages. This is true of investment in both advanced and emerging economies, with the key difference being the date and income level at which the investment rate peaks. We also observe increasing shares of services in GDP and declining shares of agricultural goods in GDP, though again the timing of these changes depends on the stage of economic development. Finally we observe capital flows to emerging markets in the early 1990s that coincides with an increase in the investment rate in those economies.

We calibrate our model to macroeconomic data. The key differences between the two regions is that emerging markets start their path of economic development at a later point in time, with a lower capital stock and a less productive labor force. All other parameters governing economic growth, sector-specific production and utility functions are identical across the two regions. The model fits the data quite well, matching the timing and peak of the investment humps, the paths of sectoral change as well as the magnitude of capital flows at the time of capital market liberalization.

We then use our model to examine two counterfactuals. The first is an analysis of the welfare gains to the two regions were capital liberalization to occur at different points in time. Because we have a multi-good model, we examine compensating and equivalent variation measures of welfare that take into account dynamic changes in relative prices. We find that both regions prefer to liberalize earlier than later – the difference in autarky interest rates diminishes over time as emerging markets catch up to advanced economies, and therefore the mutual gains from trade fall over time. Interestingly, we find that the developing economies capture the lion's share of welfare gains, though the differential between welfare gains to the two regions falls with time.

The second experiment is to consider the impact of China's integration into global financial markets. We model this as creating a new opportunity for both advanced and emerging markets to earn a higher rate of return on capital investment in China. Again, both regions gain, but China's opening redistributes capital away from emerging markets toward China. Because advanced economies are already a net creditor in global financial markets, the increase in the global interest rate generates a positive wealth effect and an increase in demand for non-traded goods and services.

CHAPTER III

Financial Crises and Income Inequality: Evidence from the U.S Great Recession

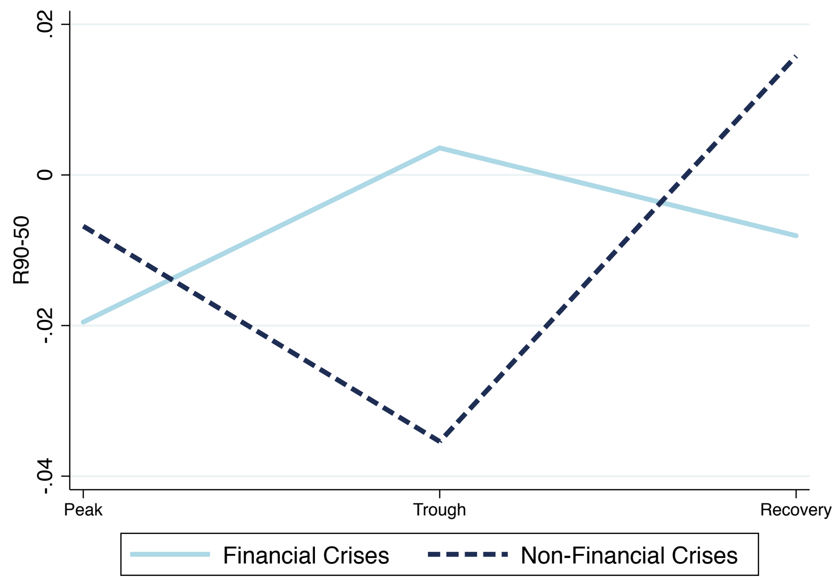
There is one well known fact: labor income inequality has increased over the past thirty years (Autor et al., 2008; David et al., 2016). Given the severity of financial crises (Reinhart and Rogoff, 2009), it is worth asking if these types of episodes can potentially explain part of the variation in labor income inequality. One potential reason to believe this is the case is that firms with heterogeneous restrictions to financing options may have differentiated responses in terms of labor demand, thus changing the distribution of wages. Therefore, in this paper I investigate how does income inequality change with financial crises and are these changes different from other types of recessions? In particular, I study if the distribution of wages is differentially affected by the severity of the financial crisis.

To motivate this question, Figure 3.1 compares the 90-50 ratio of labor income between financial and non-financial crises for a set of episodes [1], during the Peak, Trough and Recovery of the recession. This figure suggests that the cyclical behavior of labor income inequality differs between types of crises. After both types of crises the

[1] Financial Crises: U.S 2007, Austria 2008, Spain, 2008 following Reinhart and Rogoff (2008a), and Non-Financial Crises: Chile 2007, Portugal 2008, Portugal 2010, Belgium 2011, Czech Republic 2011, Finland 2011, Hungary 2011, Norway 2012.

gap between top earners and the middle class increases.[2] However, during financial crises, labor income inequality increases between the peak and the trough, whereas in non-financial crises this difference goes down.

Figure 3.1: Labor Income Distribution in Financial v.s Non-Financial Crises across Countries



Note: Using data from ILOSTAT from OECD countries on wages by occupations during the 2000 decade, and U.S weights of occupation by deciles, I construct the average linearly de-trended 90-50 ratio for Financial Crises: U.S 2007, Austria 2008, Spain, 2008 following Reinhart and Rogoff (2008a), and Non-Financial Crises: Chile 2007, Portugal 2008, Portugal 2010, Belgium 2011, Czech Republic 2011, Finland 2011, Hungary 2011, Norway 2012. The horizontal axis shows the three different moments of the recession: Peak, Trough and Recovery following Calvo et al. (2006a). The peak is the moment with the maximum cyclical component of yearly GDP using the HP filter with a smoothing parameter of 100 between two recessions. The recovery is the moment when GDP recovers its trend value, and the trough is the moment between peak and recovery with the minimum cyclical component.

Although suggestive, due to sample size and institutional differences, it is not possible to quantify the effect of financial crises on labor income inequality using cross-country evidence. Therefore, I exploit the cross-sectional variation at the county level in the United States during the Great Recession, 2007-2015. I use data from the *American Community Survey* (ACS) to measure different deciles of weekly labor income, and declines in housing net worth to measure the intensity of the financial

[2] By top earners I understand the cut-off value of the 90th percentile of wages. Notice that I do not consider other sources of income, e.i: dividends and stocks

crisis (Mian and Sufi, 2014). I document five facts that characterize the pattern of labor income inequality during the financial crisis. First, I find that the ratio of the 90th to the 50th percentile of wages increases during and after the crises in counties where the crisis was more severe. Second, the reason explaining these changes on the 90-50 ratio differs across moments of the recession.[3] Between the peak and the trough, the changes are driven by increases in top decile of the income distribution, whereas between the peak and the recovery the changes are driven by decreases in the median income. Third, I do not find evidence about unemployment driving the results. That is, when I only consider full year workers, I find similar results to the full sample. Fourth, using average weekly labor per decile, I decompose the 90-50 ratio in between and within sectors inequality, and I find that these results occur within industries, rather than between industries. Fifth, using a similar decomposition by occupations-skills, I find that changes in wages by occupation-skills can explain most of the variation.

Mian and Sufi (2014) and Mian and Sufi (2010) find that the last financial crisis was characterized by large declines in housing net worth. Therefore, I measure the severity of the crises by the percentage change of households net worth due to changes in housing prices during 2006 and 2009. To deal with possible endogenous relationship of housing prices and wages, due to supply side shocks or reverse causality (Kumhof et al., 2015), I use Saiz's (2010) housing supply elasticity as instrument. That is, an index of the ease in which housing can be expanded in a particular metropolitan area because of geographical characteristics. With this tool in hand, I find that the

[3] Following Calvo et al. (2006a) the peak is the moment with the maximum cyclical component of yearly GDP using the HP filter with a smoothing parameter of 100 between two recessions. The recovery is the moment when GDP recovers its trend value, and the trough is the moment between peak and recovery with the minimum cyclical component.

household net worth of an average county on my sample declined by 8.6%, which translates in a 3.6% increase in the 90-50 ratio between the peak and the trough of the recession, and 5.2% between the peak and the recovery. To contextualize the magnitude of the effect, the average annual growth rate of the 90-50 ratio at the national level was 0.7% during the 1980's, 0.37% during the 1990's, and 0.3% during 2000's prior the crisis.[4] My results show that the annual growth rate between the peak and trough was twice as much as the annual growth rate during the eighties. In addition to this result, I do not find evidence about economically or statistically significant changes between other parts of the distribution. Moreover, these results persist even after removing linear trends on the inequality measurements.

After establishing that differences between the top earners and the median of the distribution increased during the Great Recession, I explore possible reasons underlying these effects. First, I repeat my analysis for changes in labor income at each corresponding decile.[5] I find that on average the 90th percentile increased by 3.1% between the peak and the trough, whereas the median income decreased by roughly 3% between the peak and the recovery. This result is in line with Hershbein and Kahn (2018) who find that demand for high skill workers increased during the financial crisis.

One potential explanation for the increments in the 90th percentile are a possible compositional effects. That is, given large declines in employment, the increments on the 90th percentile could potentially be driven by higher productivities of workers who remained employed during the crises. To address this concern, I repeat my analysis only considering workers who reported working more than 50 weeks per year. I find

[4] Using data from the March Current Population Survey

[5] I understand by labor income weekly wage

a slightly stronger coefficient on the 90-50 ratio, and similar coefficients on the 90th and 50th percentiles. Thus, I can conclude that the movements of the distribution on wages are not driven by compositional effects, but by changes in the cut-off values.

Saying that labor income increases during the crisis for those at the 90th percentile of the distribution seems puzzling, and requires further analysis. First, Philippon and Reshef (2012) find evidence about dispersion between wages of the financial sector and other sectors. This evidence suggests that the differences could potentially be explained by different labor demand across sectors. On the other hand, Hershbein and Kahn (2018) provide empirical evidence about increasing demand for high skills during and after the recession. They conclude that the financial crisis was an event that amplified the effects of skill biased technological change. In this sense, their idea of this mechanism is the following. From Hershbein and Kahn (2018) and Krusell et al. (2000) there is evidence about different complementaries between capital and labor skills. Thus, firms that were not financially constrained during the crisis were able to increase investment and hire more skilled workers, rising wages of the 90th percentile. On the contrary, constrained firms were not able to invest and hired low skill workers. After the crisis, financial constrains declined and previously unconstrained firms could invest again, increasing capital, demand for skilled workers, thus reducing wages for unskilled workers.

To test the first mechanism, differences in sectoral responses to the crisis, I redefine my decile ratio as the ratio between the average wage of the 90th percentile and the average wage of the 50th percentile.[6]. After this, I decompose changes in inequality

[6]I consider that a worker belongs to the 90th percentile if her income is larger than the 80th percentile and not greater that the 90th percentile. Similarly, I consider a worker in the 50th percentile if her wage is greater than the 40th percentile and does not exceed the 50th percentile

in between and within sectors inequality (Cotton, 1988). I find that the variation on labor income inequality occurs within industries, instead of between industries, thus ruling out a possible sectoral mechanism.

From recent literature there is some suggestive evidence about the second channel, changes demand for occupation-skills. For instance, Greenstone et al. (2014) provide cross-sectional evidence about how small and more financially constrained firms significantly reduced their borrowing. Further, they find that this reduction in credit of small firms declined employment. Second, Abowd et al. (1999) find that more productive firms hire more productive workers. Third, Hershbein and Kahn (2018) find that firms that increased demand for higher skills also increased investment in new technologies. To test this hypothesis I decompose the 90-50 ratio in terms of occupations-Skills. I find evidence suggesting that changes in inequality occur because of differences in demand for High-Skill and Low-Skill occupations. Moreover, if I decompose occupation-skills in terms of the 50th and 90th percentiles, I find that the importance of Low-Skill occupations in the 90th percentile decreased throughout the crisis.

Related Literature

In this paper, I contribute to two branches of the literature: characterization of financial crises (Reinhart and Rogoff, 2008a; Khan and Thomas, 2013; Mian and Sufi, 2014; Hershbein and Kahn, 2018), and relationship between business cycles and increasing inequality (Autor et al., 2008; Song et al., 2018; Krusell et al., 2000; Quadrini and Ríos-Rull, 2015; Coibion et al., 2017; Heathcote et al., 2010; Barlevy and Tsiddon, 2006). Among the first group, characterization of financial crises, my paper closely follows papers that empirically identify the consequences of the labor market during the Great Recession in the United States (Hershbein and Kahn, 2018; Adelino et al., 2015). In particular, I closely follow the empirical strategy of Mian and Sufi (2014). They find that counties that experienced more severe losses in housing prices -deeper financial crisis- also experienced larger loses in employment in non-tradable sectors. Hershbein and Kahn (2018) add to this finding by providing evidence about vacancy posting during the recession. Their results suggest a structural change in demand for labor and capital after the Great Recession. Using an instrumental variable approach, they find that firms in more affected MSA's increased their demand for high-skill workers, accompanied with higher investment on new technologies. My finding that the 90th percentile increased in more affected counties between peak and trough is in line with this result. Moreover, by providing evidence about declines in the 50th percentile and the occupation-skill component of it after the recession, my paper suggests that the Great Recession can represent a structural change in demand for skills (Krusell et al., 2000; Song et al., 2018).

In addition, my paper contributes to papers that quantify the effects of financial crises in a general equilibrium setting (Khan and Thomas, 2013; Midrigan and Xu, 2014; Ates and Saffie, 2016; Queralto, 2016). This literature studies two particular features of financial crises. First, Khan and Thomas (2013) and Midrigan and Xu (2014) using heterogeneous agents models are able to capture how financial crises have slower recoveries and greater loses on output compared to other recessions. In both settings, financial factors such as borrowing constraints or financial intermediaries, play an essential role in explaining the aggregate behavior. My paper contributes to this literature by modeling the empirical regularities mentioned above: different complementaries between capital and labor skills. When I add these complementaries, I am able to characterize the patterns of labor income inequality observed in the data. My paper differs from Midrigan and Xu (2014) because they consider two different sectors of production to match empirical regularities in Developing Economies. From my empirical results, I find that most of the variation of labor income inequality occur within sectors rather than between them.

My paper is also closely related to the literature that characterizes labor income inequality during the past thirty years. Among this literature, there has been a major debate between the causes of increasing labor income inequality since the 19080's. On the one hand, some empirical results suggest that most of the increase in wage inequality during the past three decades can be explained by structural changes in demand for skills: Card and DiNardo (2002); Autor et al. (2008); Philippon and Reshef (2012); Song et al. (2018). On the other hand, some authors suggest that part of the variation can arise from the cyclical behavior. For example, Lee (1999) concludes that most of the increase of wage inequality during the 1980's can be attributed to a temporary effect: : reduction of minimum wage during the 1980's. Going further, some papers empirically address the question about changes in inequality due to business cycles fluctuations. Coibion et al. (2017) identify the effects of monetary policy shocks on consumption and income inequality concluding that the effect of monetary policy is different from zero. Heathcote et al. (2010) describe the patterns of income inequality from 1965 in the United States, and conclude that during recessions inequality increases. My paper adds to these papers by providing clearer identification and in both the effects of the crisis on income inequality and in the mechanisms underlying these facts. in particular, I make two contributions. First, my results suggest that financial crises are episodes that affect labor income inequality differentially. In the temporary effect, the 90th percentile increases, whereas after the recession the 50th percentile decreases. Second, I provide evidence on the cross sectional variation of labor income inequality in recent years.

The paper proceeds as follows. Section 3.1 describes the data, and the empirical specification. Section 3.2 presents and discusses the results. Section 3.3 concludes.

3.1 Data and Methods

3.1.1 Data

Using data from the *American Community Survey*[7], ACS, from 2006 to 2015 and Mian and Sufi's (2014) Housing Net Worth and Elasticity of Housing supply data set, I build a county level data set for the recession period. Using Calvo et al. (2006a), I identify 2007 as the year of the peak, 2009 as the trough and, 2015 as the recovery.[8]

Table 3.1: ACS vs. NIPA

	Mean	**Std. Dev**	**Mean**	**Std. Dev**
	ACS		NIPA	
Total Income Per Worker$^{\diamond}$	59947.708	1677.433	108923.558	5049.505
Wage $^{\diamond}$	50197.996	1469.661	68773.647	1433.192
Investment Income $^{\diamond}$	2785.926	228.054	20588.778	1317.605
Hours	39.372	0.426	40.283	0.601
Share of Manufacturing *	0.162	0.010	0.146	0.012
Share of Transportation and Communication*	0.070	0.002	0.059	0.001
Share of Whole Sales*	0.030	0.003	0.044	0.001
Share of Retail Sales*	0.173	0.004	0.104	0.001
Share of Professional Services*	0.303	0.010	0.365	0.015
Share of Public Administration*	0.048	0.002	0.148	0.006
Share of Other Services*	0.115	0.004	0.046	0.001
Share of Financial Sector*	0.073	0.004	0.061	0.001
Share Agriculture and Mining*	0.026	0.001	0.027	0.001

$^{\diamond}$ Income per worker, Wage and Investment income are annual per worker measures in U.S 2012 Dollars deflated with the PCE deflator
* Share of workers in each 1990 Census Industry Codes main categories

[7] I do not use county PUMA as my geographical reference to guarantee comparability with Mian and Sufi (2014) results.

[8] This means that I define a recession as a moment with negative cyclical component of GDP. The peak is the moment with maximum cyclical component between to recessions, recovery is the moment where GDP recovers its trend, and a trough is the moment between the peak and the recovery with the minimum cyclical component.

Before explaining the main variables of my analysis, it is important to discuss the sample size and its representativeness. First, from the ACS it is possible to obtain data on weekly wages, during 2006-2015 for 375 counties. Similarly, Mian and Sufi (2014) have a sample size of changes in housing net worth and elasticity of housing supply of 540 counties. After combining both sources of data, I obtain a sample of 267 counties. Despite the low number of counties, I claim that my sample still captures the main features of wages on the aggregate behavior, although, I cannot make any inference about other sources of income. Table 3.1 compares the Bureau of Economic Activity NIPA tables on total income, wages, and investment income per worker and year with the corresponding values from the ACS in my sample. Columns 1 and 2 show the mean and standard deviation from the ACS while Columns 4 and 3 show the corresponding results for the NIPA tables. Although average wages on the ACS are lower then NIPA wages and this difference is statistically different from zero, the standard deviation is simillar. This means that my analysis of differences between deciles is accurate, but some of the top deciles might be lower than they really are. The sample is very similar to the aggregate in terms of industries and hours worked.

As mentioned before, I measure the severity of the financial crisis as the change in Household net worth during 2006-2009 by county due to changes in housing prices, the *housing net worth channel*. Equation 3.1 defines this change.

$$\Delta_{06-09} HHNW_i = \frac{\big(\ln(P_{H09}) - \ln(P_{H06})\big) H_{i,06}}{HHNW_{i06}} \tag{3.1}$$

Where $\Delta_{06-09} HHNW_i$ is the *housing net worth channel* shock in county i, P_{Ht} is the housing market price index in the given county, and $HHNW_{06}$ was total household's net worth before the crisis in the same county. The first panel of Table 3.2 shows that

Table 3.2: Summary Statistics

	Mean	**Std. Dev**	**Pctile 90**	**Pctile. 5**	$\mathbb{N}$
	Households Net Worth Channel				
%Δ HH Net Worth	-8.45	10.13	0.30	-25.89	267
Elasticity of Housing Supply	1.98	0.98	3.87	0.76	267
	Inequality and Income				
Average Weekly Wage$^{\diamond}$	987.66	228.60	1436.78	721.60	1180
90th Pctile$^{\diamond}$	1797.11	428.13	2628.36	1314.18	1180
50th Pctile$^{\diamond}$	730.74	143.79	1021.69	557.62	1180
10th Pctile$^{\diamond}$	222.05	40.77	289.14	156.21	1180
R90-50*	2.46	0.26	2.91	2.08	1180
R90-10*	8.21	1.74	11.41	5.83	1180
R50-10*	3.33	0.54	4.36	2.52	1180
	% Change Inequality and Income Peak-Trough				
R90-50	0.90	7.11	11.28	-10.54	375
R90-10	8.84	13.02	29.56	-11.78	375
R50-10	7.94	11.75	28.21	-10.92	375
90th Pctile	-1.60	6.31	7.58	-12.32	375
50th Pctile	-2.50	6.05	6.95	-12.31	375
10th Pctile	-10.44	12.05	7.27	-31.12	375
	% Change inequality and Income Peak-Recovery				
R90-50	4.54	8.25	17.40	-9.35	331
R90-10	12.82	13.50	32.63	-10.85	331
R50-10	8.28	11.62	27.01	-11.79	331
90th Pctile	-0.54	7.60	13.00	-12.49	331
50th Pctile	-5.08	7.91	8.76	-17.62	331
10th Pctile	-13.36	12.67	7.76	-34.53	331

$^{\diamond}$ U.S 2012 Dollars deflated with the PCE deflator

* Ratio of income deciles using equation 3.2

the most affected counties in the sample experienced a loss in housing net worth of more than 20%. In contrast, the least affected counties did not experience changes in the housing net-worth due to prices. An average county experienced a loss in housing net worth due to prices of 8.45%. To see a further discussion of this source, see Mian et al. (2013).

Second, I measure labor income inequality as the ratio of two weekly labor income percentiles. In particular, I am interested in observing differences between the top and the middle, the top and the bottom, and the middle and the bottom of the labor income distribution. In this sense, my measurement of inequality is the ratio of weekly labor income of two different percentiles:

$$Ineq_{p_A p_B,i,t} = \frac{w_{p_B,i,t}}{w_{p_A,i,t}} \tag{3.2}$$

Table 3.2 presents summary statistics for the main inequality measurements. It is worth highlighting that regardless of the measurement of inequality, there is substantial variation on the percentage changes across counties. In particular, some counties increased the 90-50 ratio by 11% between the peak and the trough, while some others decreased this ratio by 11%. Moreover, given the structure of the data, I can compute any particular ratio of two percentiles of the distribution. Table C.2 on the Appendix shows summary statistics for additional measurements.

The advantage of using percentile ratios in comparison to the Gini coefficient is that it allows me to observe particular differences of the distribution. Palma (2011) shows how the Gini index is mostly responsive to changes in the middle of the distribution, and does not capture differences in the extremes. Also, using deciles ratios allows me to decompose and identify specific sources of changes, in contrast to other inequality measurements such as the Gini or entropy measurements (Cowell, 2011).

The ACS survey between 2006 and 2015 provides information about the source of income and number of weeks worked per year. The structure of the survey generates two particular characteristics of the data. First, labor, financial and business income are top and bottom coded at a different level per state and year. Following Autor et al. (2008), top coded earnings are multiplied by 1.5. Second, the ACS is conducted throughout the year and asks the participants to report the their income during the past year. This means that respondents in January are going to report their income of the calendar year before the survey was conducted while respondents on December report the their income on the corresponding calendar year. To consider this difference I use the Census Bureau adjustment factor as an additional robustness. Finally, the ACS survey reports nominal earnings. Given the absence of county level price indexes, I use two alternate options. First, following Autor et al. (2008), I use the Personal Consumptions Expenditure (PCE) deflator at the national level. In addition I use the GDP deflator at the state level as a robustness check. These adjustments are going to be relevant to observe changes in percentiles, but the do not affect ratios by county. Also, following Autor et al. (2008), I use weights for all inequality measurements.

One possible disadvantage of measuring income inequality with income ratios is that it does not allow for zero income respondents to be included in the sample. Therefore, I only include respondents with nonzero weekly earnings. Given that during the recession, unemployment increased dramatically (Mian and Sufi, 2014; Calvo et al., 2012) my measurement of inequality can underestimate the changes in labor income inequality due to a compositional bias. To address this situation, I identify workers in the sample who reported working more than 50 weeks, and recompute the income ratios for those groups. It is important to highlight from Table C.1 on the Appendix, that on average, workers reported 47 weeks of employment per year, and 76% of the sample reports working more than 50 weeks per year.

3.1.2 Empirical Model

To quantify the effect of financial crises on labor income inequality, I first estimate changes in the corresponding decile ratio between the peak and the trough. To do so, I use log difference income inequality between 2007 and 2009. Equation 3.3 shows my main specification.

$$\Delta_{07-09} Ineq_i = \beta_1 \Delta_{06-09} HHNW_i + X_i \beta + \epsilon_i \tag{3.3}$$

Where the coefficient of interest is β_1 that measures the elasticity of labor income inequality to the severity of the crises. To ease the interpretation of β_1, I multiply $\Delta HHNW_i$ by minus one. In this sense, a positive coefficient means that inequality increases with the severity of the crisis. I use as additional controls, X_i, peak levels of percentage of homeowners, race, schooling level as high-school and no-high-school, and industry shares.[9]

Given possible supply side shocks that simultaneously affected wages and housing prices, in particular in the construction sector,or possible reverse causality (Kumhof et al., 2015) I use an instrumental variable approach.[10] Saiz (2010) estimates an index of housing elasticity using geographical characteristics at a metro area, and

[9] I divide workers in nine industries: Agriculture and mining, Manufacturing and Construction, Whole Sales, Retail Sales, Professional Services, Public Administration, Finance, and Other Services.

[10] To see further discussion of the instrument and its construction please see Mian and Sufi (2010); Mian et al. (2013); Mian and Sufi (2014)

that Mian and Sufi (2014) matches at the county level. A low elasticity of housing supply county is one where due to geographical conditions, it is hard to expand the housing supply. This means that low elasticity counties were those that experienced higher increments in housing prices, thus sharper declines during the crisis.

One potential concern to identification is that each county experienced differentiated demand shocks that could potentially explain the increase in housing prices (Davidoff et al., 2016). There are three reasons to believe that the identification using Saiz's (2010) elasticity is still valid. First, Davidoff et al. (2016) argues that underlying inequality and preferences for certain amenities could potentially explain differences in demand across counties. Therefore, during the housing boom between 2000-2006, we should have observed different patterns in migration across counties, in particular, to places with more amenities. Aladangady (2017) argues that there is no evidence about significant changes in population growth, which is in line with Mian et al.'s (2013) evidence. Second, it is possible to think that places with certain amenities, like beaches, could attract high skill workers and increase prices differentially (Gyourko et al., 2013). If this was the case, we should have observed demand for mortgages and houses coming from wealthier individuals. Mian et al. (2017) provide evidence about the lenders characteristics that drove the housing boom. They find that individuals in the lowest deciles of the credit scores distribution were those increasing demand for mortgages and houses. Third, Glaeser et al. (2008) show that low elasticity places are more likely to experience asset bubbles, thus rising housing prices differentially. However, in line with Mian et al. (2017) and Aladangady (2017), there is enough evidence about low interest rates not being the a fundamental driver of the change in prices.

In sum, to correct for the possible endogenous relationship I estimate Equations 3.4 and 3.5 using Saiz (2010) elasticity of housing supply as instrument for the intensity of the financial crises, that is, changes in housing net worth due to housing prices.

$$\Delta_{06-09} HHNW_i = \gamma E_{HS} + X_i \Gamma + \upsilon_i \tag{3.4}$$

$$\Delta_{07-09} Ineq_i = \beta_1 \Delta_{06-09} H\hat{H}NW_i + X_i \beta + \epsilon_i \tag{3.5}$$

Finally, to study the long term consequences of the financial crises I maintain the specification on Equation 3.5 but instead I measure changes in income inequality as the log change of the inequality measure between the peak and the recovery. Using Calvo et al.'s (2006a) methodology I identify 2015 as the year of the recovery:

$$\Delta_{07-15} Ineq_i = \beta_1 \Delta_{06-09} H\hat{H}NW_i + X_i \beta + \epsilon_i \tag{3.6}$$

I interpret a positive coefficient on equation 3.6 as evidence of a permanent effect of the financial crises on increasing labor income inequality. In addition, to give a more precise idea of how the effects of the financial crises affect labor income inequality, I use Jordà (2005) projections of yearly changes to calculate impulse response functions. That is, local projections of each period rather than a VAR.

3.2 Empirical Results

3.2.1 Changes in labor income inequality

Peak-Trough

Table 3.3 presents the main results of the paper. Column (1) shows the first stage. The remaining columns estimate the elasticity of Income Inequality on the Ratio 9050 (R9050) using first OLS, Columns (2)-(3), and then 2SLS. Regardless of the specification, the sign of the coefficient of interest is positive. This means that as a counties experience a more severe crisis income inequality increases. I interpret the change in magnitude from the column (1) to (5) as evidence of endogeneity. Due to supply side shocks differences in and prices were decreasing simultaneously, reducing the magnitude of the OLS coefficient. On average, the difference between the R9050 increased by 3%[11] between the peak and the trough of financial crises. During the peak, on average, the the income of the 90th percentile was 7.5 times larger than the income of the 50th percentile. By the middle of the crises this difference increased to 7.9. To put this in perspective, during the decade of 1990 income the R9050 ratio was annually increasing on average 0.3%, meaning that during the financial crises income inequality increases two times faster than in normal times.[12]

The immediate question given previous results, is the effect of crisis across the distribution of income. Figure 3.2 shows the results using different decile ratios. In particular, I compare changes between the top decile of wages with every other decile. From this figure, there are two important conclusions. First, there are no changes between the top deciles, that is $90 - 80$ and $90 - 70$ ratio. Not only the magnitude

[11] On average, a county decreased its household net worth by 8.6%

[12] Using CPS data the average annual change on labor income inequality in the ratio 9050 for the United States is 0.3%

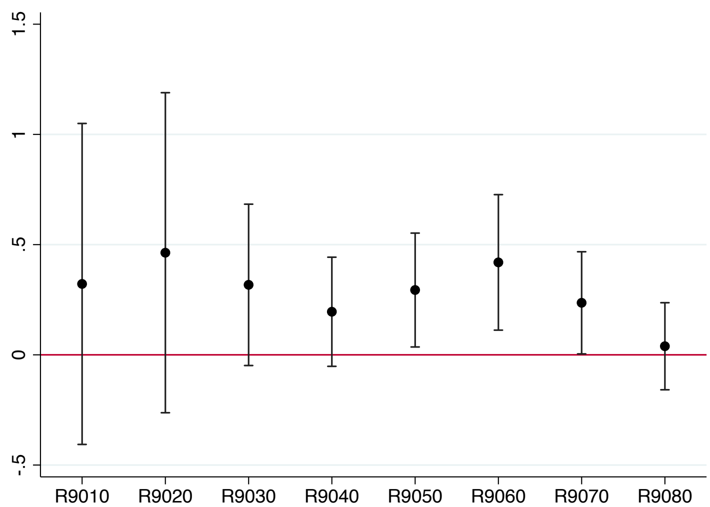
Table 3.3: Effect of Financial Crises on High Labor Income Earners and the Middle Class, $R9050$

	First Stage	Dependent Variable: $\Delta_{07-09}I_{9050}$			
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	2SLS	2SLS
Δ HH Net Worth		0.06100***	0.04859*	0.26018**	0.26681**
		(0.017)	(0.028)	(0.097)	(0.123)
White	-0.19830*		0.02034		0.06621
	(0.100)		(0.035)		(0.044)
Home owners	0.07899		0.05279		0.03183
	(0.061)		(0.044)		(0.046)
Urban	0.02980		0.02485		0.01522
	(0.049)		(0.034)		(0.039)
Constant	0.38488	0.00561	-0.44024*	-0.01121	-0.48461
	(0.299)	(0.004)	(0.258)	(0.007)	(0.289)
Industry Shares	YES	NO	YES	NO	YES
Schooling Shares	YES	NO	YES	NO	YES
N	267	267	267	267	267

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-09}I_{9050}$, on Changes in Housing Net Worth, Δ HH Net Worth. Column 1 reports the first stage using equation 3.4. Columns 2 and 3 report OLS estimates using equation 3.3. Columns 4 and 5 report the 2SLS estimates using equation 3.5. Industry shares correspond to 1990 Census Industry Codes main categories: Manufacturing and Construction, Agriculture and Mining, Whole Sales, Retail Sales, Professional Services, Transportation and Communication, Public Administration, Financial Sector, and Other Services. Schooling shares are the average workers with and without High School Diploma. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of the coefficient is close to zero, but the results are not statistically significant. Second, it is not possible to conclude that there are significant differences in the change in inequality between the 90th percentile of income and the bottom. Thus, I conclude , that there is significant evidence that during the Great Recession there were temporary increments in the difference between the top decile and the median of the distribution. Moreover, Figure C.1 on the Appendix compares the effects changes between the 50th percentile with lower deciles. Similarly to these results, there is no evidence of changes in the distribution.

Figure 3.2: Effect of Financial Crisis Across the Distribution of Income



Note: The vertical axis shows the estimated coefficients of equation 3.5 for different deciles ratios during the peak and trough and their corresponding confidence intervals at a 95% significance level. The horizontal axis shows the each decile ratio. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level

Finally, due to increasing patterns of labor income inequality (Card and DiNardo, 2002; Autor et al., 2008; Philippon and Reshef, 2012; Song et al., 2018), there is a possible concern that my estimates are capturing the effect of these trends. To control for this possibility, I linearly de-trend the $90-50$ ratio for each county.[13] Column 4 of table 3.4 shows the point estimate of this result. Although smaller, I still find a positive and significant effect of the crisis on the $90-50$ ratio. From results not reported in the paper, the effects are similar in the rest of the distribution. Besides linearly detrending, I also modify each inequality measurement using state level GDP deflators, and IPUMS adjust factor, columns 2-3 from table 3.4. In addition to all of the above, I modify my measurement of inequality de-trending, adjusting for state rather than national prices, and using IPUMS adjust factor. Column 5 of table 3.4 shows this result. Not only the effect remains but the point estimate is higher.

Table 3.4: Robustness

	(1)	(2)	(3)	(4)	(5)
	$\Delta_{07-09}I_{9050}$	$\Delta_{07-09}I_{9050_D}$	$\Delta_{07-09}I_{9050_A}$	$\Delta_{07-09}I_{9050_L}$	$\Delta_{07-09}I_{9050_{F3}}$
HH Net Worth	0.26681**	0.26681**	0.26681**	0.23040*	0.32906**
	(0.123)	(0.123)	(0.123)	(0.118)	(0.139)
N	267	267	267	267	267

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-09}I_{9050}$, on Changes in Housing Net Worth, Δ HH Net Worth using using using equation 3.5 . Column 1 reports the benchmark result. Column 2 uses $R90-50$ with State Level GDP deflator as dependent variable. Column 3 uses $R90-50$ with IPUMS Adjust factor as dependent variable. Column 4 uses linearly de-trended $R90-50$. Column 5 uses linearly de-trended, IPUMS Adjust factor and State level GDP deflator $R90-50$ as dependent variable. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Peak-Recovery

I established evidence about the temporary effect of the Great Recession on increasing in the difference between the 90th and the 50th percentile of labor income. Now, I explore whether this change was permanent. To do so I use two different approaches. First, Table 3.5 shows how the $90-50$ ratio changes between the peak and the recovery of the recession, that is between 2007-2015. I find a positive and

[13] To guarantee comparability in magnitudes, I take logs before removing the trend, and take differences after detrending

significant result. Following the same analysis as before, on average the difference between the top labor income earners and the middle class increase by 3.5%. Recall that the change during the Peak and the Trough was around 3%. I interpret this result as evidence that most of the change in labor income inequality due to the financial crises occurs at the begging of the recession, that is between the peak and trough, but this change is persistent over time.

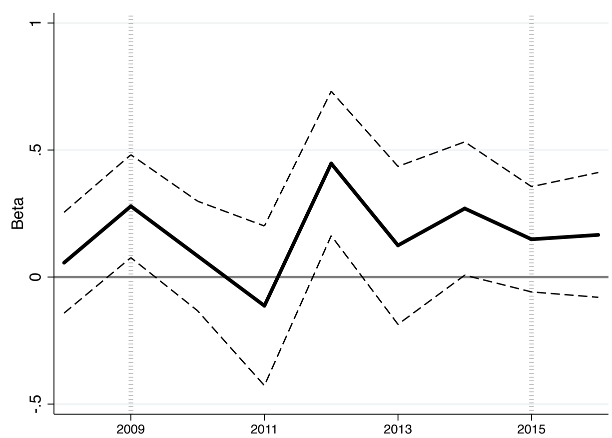
Table 3.5: Effect of Financial Crises on High Labor Income Earners and the Middle Class, $R9050$

	First Stage	Dependent Variable: $\Delta_{07-09} I_{9050}$			
	(1)	(2)	(3)	(4)	(5)
		OLS	OLS	2SLS	2SLS
Elasticity	-0.03313***				
	(0.010)				
Δ HH Net Worth		0.15628***	0.16060**	0.26961***	0.51597**
		(0.040)	(0.062)	(0.097)	(0.201)
White	-0.18338*		-0.01648		0.06812
	(0.093)		(0.044)		(0.081)
Howw owners	0.11482		-0.09576*		-0.14900*
	(0.083)		(0.053)		(0.080)
Urban	0.00676		0.02624		0.03108
	(0.045)		(0.053)		(0.049)
Constant	-0.08771	0.03632***	0.23179	0.02648***	0.39346
	(0.249)	(0.006)	(0.418)	(0.008)	(0.409)
Industry Shares	YES	NO	YES	NO	YES
Schooling Shares	YES	NO	YES	NO	YES
N	240	240	240	240	240

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-15} I_{9050}$, on Changes in Housing Net Worth, Δ HH Net Worth. Column 1 reports the first stage using equation 3.4. Columns 2 and 3 report OLS estimates using equation 3.3. Columns 4 and 5 report the 2SLS estimates using equation **??**. Industry shares correspond to 1990 Census Industry Codes main categories: Manufacturing and Construction, Agriculture and Mining, Whole Sales, Retail Sales, Professional Services, Transportation and Communication, Public Administration, Financial Sector, and Other Services. Schooling shares are the average workers with and without High School Diploma. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To verify the persistence of the results, I use Jordà (2005) projections to calculate impulse response functions. This are, linear projections from year-to-year variations to extrapolate the temporary effect rather than estimating a VAR. Given the concern of linear trends in inequality, I use only the linearly de-trended measurements to estimate the impulse response functions. Figure 3.3 shows these results using a 90% confidence intervals. This graph confirms my previous findings. The crisis has a permanent effect on the difference between the 90th percentile and the 50th percentile, but still persists. Table C.3 on the Appendix shows that the results are robust to different measurements of inequality.

Figure 3.3: Impulse Response 90-50 Ratio

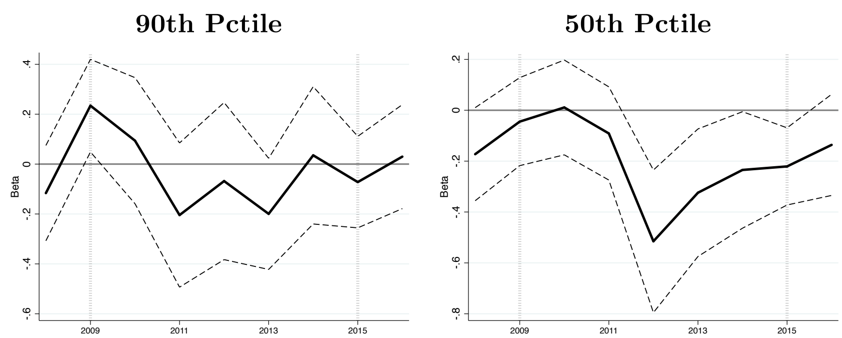


Note: Impulse Response functions of the $90-50$ ratio using Jordà (2005) projections for years 2008, 2009, 2010, 2011, 2012, 2013, 2014, and 2015 from equation 3.5 . Vertical lines indicate the peak and recovery years correspondingly. Confidence intervals at the 90% significance levels. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level

3.2.2 Income deciles and compositional effect

The following step is to understand the reasons underlying the change in the $90-50$ ratio. To do so, I quantify the changes in each of the corresponding income deciles. Figure 3.4 shows the impulse response functions of the linearly de-trended 90th and the 50th percentiles of income. From this graph it is possible to conclude that the reason underlying the change differs across moments of the recession. First, when the shock hits, inequality increases because the 90th percentile of income increases. It is important to clarify that given the structure of my data I can not identify if there are compositional differences in each decile. That is, it is possible that those individuals at the 90th percentile before the crisis do no longer belong to this percentile. Therefore, my result suggests that the cut-off value of the 90th percentile increases between the peak and the trough, but I cannot conclude that the 90th percentile has the same composition of individuals. Hershbein and Kahn (2018) find that during the crisis demand for higher skills increase. Therefore, one possible explanation for a higher 90th percentile is that demand for high-skill workers increases between the peak and trough of the recession.

Figure 3.4: Impulse Response Functions for the 90th and 50th Percentiles of Labor Income



Note: Impulse Response functions of the 90th percentile, left panel, and the 50th percentile, left panel, using Jordà (2005) projections for years 2008, 2009, 2010, 2011, 2012, 2013, 2014, and 2015 from equation 3.5. Vertical lines indicate the peak and recovery years correspondingly. Confidence intervals at the 90% significance levels. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level

On the other hand, after the recession ends I observe that the 50th percentile declines. It is also important to notice the effect on the 90th percentile goes is not permanent. This result is in line with Mian and Sufi (2014) and Calvo et al. (2012), who find that employment slowly recovers after the crisis. If lower skilled workers lose more jobs during the crisis, and these jobs slowly recover after the recession, it is reasonable to argue wages go down due to excess supply. Therefore, these results suggest that there is evidence of more demand of high skill workers during the crisis, with excess supply of low skill workers after the recovery.

Table 3.6: Compositional Effect: Changes in Income and Employment Peak-Trough

	(1)	(2)	(3)
	A. Full Sample		
	$\Delta_{07-09}I_{9050}$	$\Delta_{07-09}W_{90}$	$\Delta_{07-09}W_{50}$
Δ HH Net Worth	0.26681**	0.28259*	0.01578
	(0.123)	(0.141)	(0.090)
	B. Only workers with $weeks > 50$, $F2$		
	$\Delta_{07-09}I_{9050_{F2}}$	$\Delta_{07-09}W_{90_{F2}}$	$\Delta_{07-09}W_{50_{F2}}$
Δ HH Net Worth	0.32906**	0.29958**	-0.02948
	(0.139)	(0.144)	(0.088)
N	267	267	267

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-09}I_{9050}$, column 1 of panels A and B, on Changes in Housing Net Worth, Δ HH Net Worth using using equation 3.5. Columns 2 and 3, report changes on the 90th,W_{90} and 50th, W_{50} percentiles using equation 3.5. Panel A reports results using all workers from the sample. Panel B reports results with workers that reported more than 50 weeks per year, $F2$. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

One immediate concern is the possible existence of a compositional effect. Given that I measure labor income inequality with weekly income, it is possible that my result is driven by changes in the number weeks worked. Moreover, Mian and Sufi (2014) and Calvo et al. (2012) find that the financial crisis of 2007-2015, and in general financial crises in developed economies, are characterized by large declines in employment. To control for this possible effect, I restrict my sample to workers who report working more than 50 weeks per year, $F2$ workers in Table 3.6, Panel B. My result is robust to this restriction. I interpret this result as evidence that changes in employment do not drive changes in labor income inequality. More importantly, increments in the 90th percentile of income are not related to changes in employment. In addition, Table C.4 on the Appendix, shows that changes in overall employment for the 90th percentile of income are small and not statistically significant. Also, to have an idea of the importance of employment after the recovery, I repeat the analysis with changes of inequality and both income deciles between peak and recovery. Table C.5 on the Appendix show that the results are consistent.

3.2.3 Within and Between Industries Inequality

One potential mechanism driving changes in inequality and different effects on the 90th and 50th percentile during the crisis is that sectors were differentially affected during the crisis. For instance, Philippon and Reshef (2012) find evidence about dispersion between wages of the financial sector and other sectors. This evidence suggests that changes in inequality could potentially be explained by different labor demands across sectors. Also, one could think that some services, like education, health and lawyers, were not affected by the crisis, therefore their wages increased. On the other hand, workers in manufacturing could have experienced disproportionately large loses (Mian and Sufi, 2014).

To test this possible mechanism, I redefine my decile ratio as the ratio between the average wage of the 90th percentile and the average wage of the 50th percentile. I consider that a worker belongs to the 90th percentile if her income is larger than the 80th percentile and not greater that the 90th percentile. Similarly, I consider a worker on the 50th percentile if her wage is greater than the 40th percentile and does not exceed the 50th percentile. Therefore, the inequality ratio is defined as follows:

$$\bar{I}_{9050} = \frac{\bar{W}_{90}}{\bar{W}_{50}} = \frac{\sum_{i=1}^{N_{90}} w_{i,90}}{\sum_{i=1}^{N_{50}} w_{i,50}} \tag{3.7}$$

I then decompose the changes in inequality in between and within sectors inequality (Cotton, 1988). To do so, I divide the economy in nine sectors: manufacturing, agriculture and primary activities, and seven services sub-sectors, public administration, financial Sector, transportation & communication, whole sales, retail, professional activities, and other services. This decomposition implies that changes in wages can be explained by differences between and within sectors. Equation 3.8 shows change in wages decomposition, where i are individuals, p percentile of income, j sector, and t period:

$$\Delta \ln(\bar{W}_{p,t+1}) = \underbrace{\sum_j \frac{\alpha_{j,t}\Delta \ln(\bar{w}_{p,j,t+1})}{\bar{W}_{p,t}}}_{Within} + \underbrace{\sum_j \frac{\bar{w}_{p,j,t}\Delta \ln(\alpha_{p,j,t+1})}{\bar{W}_{p,t}}}_{Between} \tag{3.8}$$

Where $\bar{W}_{p,t+1} = \frac{\sum_{i=1}^{N_p} w_{i,p,t+1}}{N_{p,t+1}}$, , $\bar{w}_{p,j,t} = \frac{\sum_{i=1}^{N_{p,j,t}} w_{i,p,j,t}}{N_{p,j,t}}$, and $\alpha_{p,j} = \frac{N_{j,p}}{N_p}$

Then I define inequality growth as the log difference between the 90th percentile minus the 50th percentile:

$$\begin{aligned} \Delta \ln(\bar{I}_{9050,t+1}) =& \Delta \ln(\bar{W}_{90,t+1}) - \Delta \ln(\bar{W}_{50,t+1}) \\ =& \underbrace{Wt_{90,t+1} - Wt_{50,t+1}}_{WithinInequality} + \underbrace{B_{90,t+1} - B_{50,t+1}}_{BetweenInequality} \end{aligned} \tag{3.9}$$

Therefore, I understand changes in inequality between sectors as the difference of changes of between sectors wages in the 90th and 50th percentile. Similarly, changes in inequality within sectors are the difference of wage changes in the 90th and 50th percentile within sectors. The first three columns of Table 3.7 show the decomposition during the peak and trough, while the remaining three columns show it for the peak and recovery. In both cases, I find that most of the variation on labor income inequality occurs within industries, rather than between industries. To further understand this result, Figure C.4, shows the estimated coefficients of each component

Table 3.7: Between and Within Industry Inequality

	Peak-Trough			Peak-Recovery		
	$\Delta_{07-09}\bar{I}_{9050}$	$\Delta_{07-09}Wt_{9050}$	$\Delta_{07-09}B_{9050}$	$\Delta_{07-15}\bar{I}_{9050}$	$\Delta_{07-15}Wt_{9050}$	$\Delta_{07-15}B_{9050}$
HH Net Worth	0.29919**	0.21553**	0.08366	0.58935**	0.38134**	0.20800*
	(0.145)	(0.091)	(0.077)	(0.243)	(0.150)	(0.115)
N	267	267	267	240	240	240

Note: This estimates equation 3.5 using measurements from equation 3.9. $\bar{I}_{9050}$ is average change in inequality, B_{9050} is between sectors inequality, and Wt_{9050} is within sectors inequality. First three columns estimate this change between the Peak and Trough, 2007-2009. Last three columns estimate this change between Peak and Recovery, 2007-2015. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of the Within inequality term in equations 3.7 and 3.8 between peak and trough[14]. From the figure it is possible to conclude that each industry has similar importance on changes in the 90-50 ratio. Moreover, Figure C.3 on the Appendix reinforces this result by showing that during the crisis periods -peak, trough, and recovery- all industries were similarly represented in each decile. Meaning that it is not possible to conclude that one particular industry is contained in one percentile.

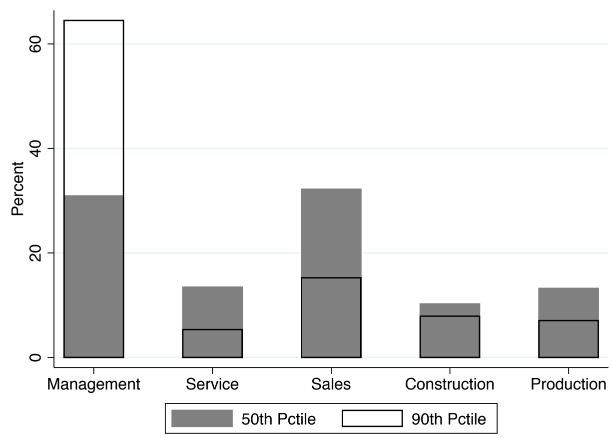
3.2.4 Within and Between Occupations Inequality

A second potential mechanism to explain changes in the 90-50 ratio during the recession are differences in demand for occupations-skills, and the corresponding composition of each decile by those occupations-skills. Hershbein and Kahn (2018) provide empirical evidence about increasing demand for high skills during and after the recession. They conclude that the financial crisis was an event that amplified the effects of skill biased technological change. In this sense, the idea of this mechanism is the following. From Hershbein and Kahn (2018) and Krusell et al. (2000) there is evidence about different complementaries between capital and labor skills. Thus, firms that were not financially constrained during the crisis were potentially able to

[14]The results are similar for Peak-Recovery, but are not reported in the paper

increase investment and hire more skill workers, rising wages of the 90th percentile. On the contrary, constrained firms were possibly not able to invest hiring low skill workers. After the crisis, financial constraints could potentially decline and previously unconstrained firms can invest again, reducing wages for unskilled workers.

Figure 3.5: Occupation Shares



Note: This graphs shows the percentage of workers during years 2007, 2009, and 2015 in each occupation and percentile, 50th and 90th correspondingly. I classify the sample in occupations according to the SOC 2010 classification. From left to right Management, Professional, and Related Occupations (major groups 11-29), Service Occupations (major groups 31-39) , Sales and Office Occupations (major groups 41-43), Natural Resources, Construction, and Maintenance Occupations (major groups 45-49), and Production, Transportation, and Material Moving Occupations (major groups 51-53). For further details on the classification, see `https://www.bls.gov/soc/soc_2010_user_guide.pdf` . A worker belongs to the 50th percentile $w_{40} < w_i \leq w_{50}$, and a worker belongs to the 90th percentile if $w_{80} < w_i \leq w_{90}$

Figure, 3.5 gives some suggestive evidence about how occupation-skills can drive the result. Contrary from the industries case (see, Fig C.3), we can associate almost all of the 90th percentile with Management, Professional, and Related Occupations, whereas this occupation roughly represents 30% of the 50th percentile. From recent literature there is some suggestive evidence about the second part of the mechanism. For instance, Greenstone et al. (2014) provide cross-sectional evidence about how small and more financially constrained firms significantly reduced their borrowing. Further, they find that this reduction in credit from small firms declined employment.

Also, Abowd et al. (1999) find that more productive firms hire more productive workers, while Hershbein and Kahn (2018) find that firms that increased demand for higher skills also increased investment in new technologies.

To test this hypothesis I decompose the 90-50 ratio in terms of Occupations-Skills following equations 3.8 and 3.7. I classify workers to High-Skill occupations, S, if they report working in Management, Professional, and Related Occupations, which correspond to broad occupations 11 to 29 in the SOC 2010 Classification. Similarly, I classify workers to Low-Skill occupations, U, if they report working on Service, Sales, Natural Resources, Construction, Maintenance, Production, Transportation, and Material Moving Occupations. That is, Low-Skill occupations correspond to broad occupations 31 to 53 in the SOC 2010 Classification.[15] Columns 2 and 3 of Table 3.8 show each component of the within inequality. From panel A, it is possible to conclude that most of the variation between peak and trough can be explained by changes in wages of High-Skill Occupations. Similarly, most of the variation during peak and recovery also seems to be coming from reduction of wages in High-Skill Occupations.

This result seems puzzling in light of the occupation-skill hypothesis. In particular, it raises the question why are wages first increasing for high skill workers in the 90th percentile, and then decreasing in the 50th percentile for this same occupation-skill? One potential explanation for this is a mechanical result from the decomposition. Given that the criteria to be classified as part of the 50th percentile is that wages correspond to a certain rage, it is possible that my results does not capture differences in weights within each decile. Thus, I need to verify if Low-skill occupations were

[15] For further details see ,`https://www.bls.gov/soc/soc_2010_user_guide.pdf`

Table 3.8: Within and Between Occupations-Skill Inequality

	(1)	(2)	(3)	(4)
	A. Peak-Trough			
	$\Delta_{07-09}\bar{I}_{9050}$	$\Delta_{07-09}S_{9050}$	$\Delta_{07-09}U_{9050}$	$\Delta_{07-09}B_{9050}$
Δ HH Net Worth	0.21389**	0.16046**	0.05884	-0.00540
	(0.087)	(0.065)	(0.048)	(0.004)
N	267	267	267	267
	B. Peak-Recovery			
	$\Delta_{07-09}\bar{I}_{9050}$	$\Delta_{07-09}S_{9050}$	$\Delta_{07-09}U_{9050}$	$\Delta_{07-09}B_{9050}$
Δ HH Net Worth	0.35011**	0.31338**	0.04142	0.00403
	(0.155)	(0.130)	(0.038)	(0.005)
N	238	240	238	238

Note: This estimates equation 3.7 by Occupations-Skills, where S change in wages in the High-Skill Occupations, and U are change in wages for the Low-Skill Occupations. Notice that $U + S = Wt$ from equation 3.8. I classify the sample in occupations according to the SOC 2010 classification. Where High-Skill Occupations are Management, Professional, and Related Occupations (major groups 11-29), and Low-Skill occupations are Service Occupations (major groups 31-39) , Sales and Office Occupations (major groups 41-43) , Natural Resources, Construction, and Maintenance Occupations (major groups 45-49), and Production, Transportation, and Material Moving Occupations (major groups 51-53). For further details on the classification, see `https://www.bls.gov/soc/soc_2010_user_guide.pdf`. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

displaced from the 50th percentile. To address this concern, instead of decomposing each decile into occupations, I decompose each occupation into a corresponding decile. Equation 3.10 shows this decomposition

$$\Delta \ln(\bar{W}_{o,t+1}) = \overbrace{\frac{\alpha_{90,t}\Delta \ln(\bar{w}_{o,90})}{\bar{W}_{o,t}} + \frac{\alpha_{50,t}\Delta \ln(\bar{w}_{o,50})}{\bar{W}_{o,t}}}^{Within} + \underbrace{\frac{(\bar{w}_{o,90,t} - \bar{w}_{o,50,t})\Delta \ln(\alpha_{o,90,t+1})}{\bar{W}_{o,t}}}_{Between} \tag{3.10}$$

Letting occupation-skill be $o = \{S, U\}$ and percentiles $p = \{50, 90\}$, then $\bar{W}_{o,t+1} = \frac{\sum_{i=1}^{N_o} w_{i,o,t+1}}{N_{o,t+1}}$, , $\bar{w}_{o,p,t} = \frac{\sum_{i=1}^{N_{o,p,t}} w_{i,o,p,t}}{N_{o,p,t}}$, and $\alpha_{o,p} = \frac{N_{o,p}}{N_o}$

Table 3.9 shows this decomposition. From this table there are three important conclusions. First, Columns 1 and 4 show changes in wages per occupation-skill, High-Skill and Low-Skill correspondingly. From this result, it is possible to conclude that regardless of the decile, wages of High-Skill occupations increase during peak and trough, and wages of Low-Skill occupations decrease during peak and recovery. Second, Column 2 shows that within the High-Skill occupation the relevant change during peak and trough occurs within deciles, and in particular in the 90th percentile (See, Table C.6 on the Appendix), which is in line with my previous findings. Third, Column 6 shows that the importance of the 90th percentile in Low-Skill occupations decreases during peak-trough, and peak-recovery. This result suggests that the composition of the 50th percentile changed during the crisis. One possible interpretation is that during the crisis, demand for Low-Skill occupations decreased substantially that displaced these workers out of the 90th and 50th percentiles. Therefore, from the occupation analysis, there is evidence suggesting that changes in the 90-50 ratio during the financial crisis are due to differences in demand for skills.

3.2.5 Discussion and Mechanisms

The results so far imply that labor income inequality between the 90th and the 50th percentile increased during the Great Recession. Also, there is no evidence about significant changes between other parts of the distribution. However, saying that labor income increases at the 90th percentile of the distribution seems puzzling, and requires further analysis. At this stage, I ruled out two possible explanations for this change: compositional effect in employment and different responses of wages across sectors.

Another potential mechanism underlying these facts is that there are different complementarities between capital and labor, thus, constraints on the borrowing channel

Table 3.9: Within and Between Occupation-Skill Variation

	(1)	(2)	(3)	(4)	(5)	(6)
			A. Peak-Trough			
	$\Delta_{07-09}W_S$	$\Delta_{07-09}Wt_S$	$\Delta_{07-09}B_S$	$\Delta_{07-09}W_U$	$\Delta_{07-09}Wt_U$	$\Delta_{07-09}B_U$
Δ HH Net Worth	0.21050	0.24569**	-0.05632	-0.02218	0.18164	-0.21817**
	(0.170)	(0.115)	(0.100)	(0.108)	(0.111)	(0.102)
N	267	267	267	267	267	267
			A. Peak-Recovery			
	$\Delta_{07-15}W_S$	$\Delta_{07-15}Wt_S$	$\Delta_{07-15}B_S$	$\Delta_{07-15}W_U$	$\Delta_{07-15}Wt_U$	$\Delta_{07-15}B_U$
Δ HH Net Worth	0.02688	-0.04305	0.04215	-0.45354**	-0.03556	-0.39736
	(0.197)	(0.177)	(0.126)	(0.203)	(0.196)	(0.240)
N	240	240	240	240	238	238

Note: This table estimates equation 3.10. $\bar{W}_S$ is average change in High-Skill Occupations, and $\bar{W}_U$ is average change in the Low-Skill Occupations. I classify the sample in occupations according to the SOC 2010 classification. Where High-Skill Occupations are Management, Professional, and Related Occupations (major groups 11-29), Service Occupations (major groups 31-39) , Sales and Office Occupations (major groups 41-43); and Low-Skill occupations are Natural Resources, Construction, and Maintenance Occupations (major groups 45-49), and Production, Transportation, and Material Moving Occupations (major groups 51-53). For further details on the classification, see `https://www.bls.gov/soc/soc_2010_user_guide.pdf`. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of the firms can affect their labor demand decision. In particular, firms that are not financially constrained during the crisis can increase investment and simultaneously increase their demand for high-skill workers. This could potentially explain increases in the 90th percentile during the crisis. On the contrary, constrained firms are not able to invest during the crisis, due to binding collateral constraints, thus hiring low skill workers. After the crisis, financial constrains decline and previously unconstrained firms can invest reducing their demand for skill workers, thus wages. Although I cannot directly test this mechanism from my data, I find evidence that supports this mechanism. In particular, three facts support this hypothesis. First, after a decomposition of inequality by skill-occupations, I can conclude that changes in the 90th percentile occur because wages of Managerial occupations increased. Second, between peak and recovery reduction in Low-Skill occupations more than doubles the decline during peak and trough of High-Skill occupations. Third, workers in Low-Skill occupations were displaced from the 90th percentile. This also suggests that Low-Skill occupations were displaced out of the 50th percentile. Therefore, reductions in the 50th percentile occur mostly because Low-Skill workers became less important in the 50th percentile. I interpret this last result as indirect evidence of the skill-occupation hypothesis.

It is worth highlighting that in recent literature, there is suggestive evidence about the role of financial constraints by types of firms. For instance, Greenstone et al. (2014) provide cross-sectional evidence about how small and more financially constrained firms significantly reduced their borrowing during the crisis. Also, they find that this reduction in credit from small firms declined employment. In addition, Abowd et al. (1999) find that more productive firms hire more productive workers. Further research should test the behavior of small and constrained firms during the recession, and in particular their investment patterns.

3.3 Conclusions

To conclude, in this paper, I investigate the effects of the Great Recession on labor income inequality in the cross-sectional variation at the county level in the U.S. Using an instrumental variable approach, I find that differences between the 90th percentile of the distribution and the 50th percentile increased between the peak and trough, and peak and recovery. To provide some context to my results, the magnitude of the change is comparable with the increase in inequality during the 1980's. However, I do not find evidence about changes in other segments of the distribution. Second, I show that these changes occur for different reasons. Between the peak and trough, the 90th percentile of income increases, but after the recovery the 50th percentile of income decreases. I show that these results are robust to different specifications, in particular when I consider possible linear trends. Third, I rule out two possible mechanisms explaining these facts. After I restrict my sample to those workers who report working more than 50 weeks per year, the result remains in sign and significance, but the magnitude increases. Second, I decompose inequality in between and within sectors, and I do not find evidence about different responses of wages between sectors. Fourth, I find some evidence suggesting that changes in inequality occur because of differences in demand for High-Skill and Low-Skill occupations.

From evidence in the literature, it seems that one possible mechanism underlying these results is the existence of different complementaries between capital and skills, plus firms being differentially affected during the crisis by binding financial constraints. This mechanism should be tested in future research.

APPENDICES

APPENDIX A

Appendices to Chapter 1

A.1 Appendix: Data

A.1.1 Credit

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

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

We use this data as input to estimate the credit shock and to compute bank- and firm-level financial data.[1]

After removing outliers and data-entry errors as we describe above, we aggregate the data at the firm and bank levels separately. At this point, we do not consider

[1] Credit_Full_Comm_Quart.dta.

the history of each credit. Instead, we use information on the opening date of each transaction. We define the average credit amount on date t, the average interest rate, the probability of default as a dummy if the firm ever defaulted on a credit. We define the number of credits as the number of open credits at date t with all banks, and total new debt as the total amount of new debt with all banks at date t. To calculate the number of relationships per firm, we go back to the original data and keep the initial and the final date per operation and the bank. We reshape the data and count the number of open credit operations. We count as an open relationship the oldest initial date with a bank, and close the relationship if on the final date of the operation there are no more open credits with that bank.

A.1.2 Banks

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

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

Table A.1: Summary Statistics: Banks

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

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

liabilities.

To compute the banking health measures from the balance sheet, we develop a matching methodology between financial reports. First, we keep for each month and year the groups and classes, the broader classification in the financial report, and store the names of the accounts for each year. Then we merge by year the accounts classification by class and group. The goal in this step is to compare if the numeric classification corresponds to the variable description. In this sense, we compare the difference in the text description of each account with the previous year, and define a ratio as the number of variables with a different variable description between year t and year $t-1$. We identify a different accounting methodology if the difference in description between two years is greater than 12%. We find that the variable descriptions changed in 2015. Between 2014 and 2015, 81% of the descriptions are different. After identifying the differences, we manually looked for the variables of interest in each accounting methodology.

A.1.3 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

Table A.2: Summary Statistics: Banking Shock

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

Note: Summary Statistics of the credit-supply shock

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

A.1.4 *Super-Sociedades*

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

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

Variable names

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

Form matching

To compare information between methodologies, we first match the general forms (*Formatos*) using a fuzzy-merge algorithm. For each available form in 2007's methodology, we compare merge names with 2000's algorithm and consider a match by the minimum difference between the texts. Using this algorithm, we merge 29 formatos and verify manually that the remaining four do not have a correspondence in 2000's methodology. Table A.3 shows the correspondence between forms. The first two columns show the original names in Spanish for 2007 and 2000, while the last two show the corresponding numbers.

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

Table A.3: Matching General Forms (*Formatos*)

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

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

Variables of interest

This section describes the variables we keep in the final database, their general forms of origin, and how we modify them. We divide our variables of interest into four categories: general information, balance sheet, liquidity constraints, international exposure, and labor. After categorizing the information, we first keep firms that have positive values for all assets and for which the basic accounting equation holds. We do this to ensure we have no substantial data-entry errors. Second, we verify that the report on capital—fixed assets—is always positive and that it contain no outliers. Then, if capital is missing in a particular year, but the column that reports capital from the previous year is not, we replace capital in the current year as the reported capital from the previous year. At this point, we ensure that we have no negative capital values on capital. If we do, we replace the missing observation; if the previous and following years are not missing, we impute the value as the average. Third, we drop firms if sales and operational costs are negative or that report a number of workers larger than 10% of the 2010 Colombian working-age population[2] or if the total wage bill is negative. Fourth, we use sectors and cities from the public report because firms' original reports contain more data-entry errors in the sector classification and cities, whereas the public reports have been corrected. We merge the city, region,

[2]38,693,000 from DANE.

and sector by NIT and year. From the sector and location, we leave the sector and city of the first observation if it is time variant. Finally, we drop firms if total assets, liabilities, equity or sales are missing or if the age of the firm is negative. We keep firms for which we have at least four years of data with no more than a single one-year gap. We impute the values for any gaps as the average between the previous and following years. After the imputation, we drop the firms at the top and bottom 1% of assets.

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

A.1.5 Matching firms in PILA and Super-Sociedades

PILA uses worker and firm identifiers—*personabasicaid* and *id*, respectively—exclusive for this database. For 2010, the database provides a matching between the workers' identifiers, a unique pair *cédulas–personabasicaid*, but does not provide the same for firms. Therefore, our task is to match the firms' identifiers, *NIT–id*.

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

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

Step 1: Cleaning data-entry errors

Using the original match between *personabasicaid* and *cédulas*,[3] we remove data-entry errors, nonnumeric characters, and *cédulas* with fewer than eight digits.[4] We store this data as "cedulas_unicas.dta." Following a similar procedure, we use the original workers' information in Super-Sociedades.[5] and create *NIT–cédula* pairs. Again, we remove data-entry errors, nonnumeric characters, and *cédulas* with fewer than eight digits. In contrast, we assume the NITs are free of the same data-entry errors (see Data Appendix A.1.4). Here, we restrict our sample to the first three legal representatives and the main accountant. We drop information about board members, the auditor, and other legal representatives and accountants. We store this data as "cedulas_SS_all-cedulas_unicas."

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

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

On the other hand, we create an equivalent file using PILA, here we generate a *id–cédula*–personabasicaid triplet. To generate this triplet, we merge "cedu-

[3]file name: personabasicaid_allGta.

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

[5]SuperSociedades_Formato1.dta.

las_unicas.dta" with each December in PILA between 2010 and 2015. We only use December because Super-Sociedades has information about the annual financial reports, and these reports are presented on December 31 each year. We also restrict our sample to nonindependent workers with wages above minimum wage and below 0.01% of the distribution,[6] more than 15 days worked per month, and not double reported in the same firm. As before, we also store year and region–city code. We save this data as "cedulas_merge_pila'

Step 3: *NIT–id*

We use an iterative elimination process using a sequence of criteria. Regardless of the criterion used in each step, the process works as follows. First, we apply the criterion to both "cedulas_con_personasbasicaid_unicas" and "cedulas_merge_pila." We merge the databases using a one-to-one condition, keeping only those pairs that matched. Then, we verify that both *NIT* and *id* are unique, and drop the pair otherwise. We store the matches and update our information set. That is, we remove the identified *NITs* and *ids* from "cedulas_con_personasbasicaid_unicas" and "cedulas_merge_pila," respectively, and move to the following criterion. From this process, we identify 24,694 *NIT–id* pairs, 69.8% of the total firms. Of those, we recover 17,929 firms with more than two years of data, and 15,202 firms with four or more years of data. These correspond to 75.5%, and 77.2% of the total number of firms with more than 2 and more than 4 years of data.

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

1. **Unique–Unique**: We keep workers that only worked in one firm during the

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

entire period (2010–2015) in both *Super-Sociedades* and *PILA*. We merge by *cédula*. Using this criterion, we obtain 14,330 firms.

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

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

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

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

6. **Unique group of workers, city, year–Unique group of workers, city, year**: An individual could have had more than one job, and the group of workers

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

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

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

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

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

obtain 98 firms.

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

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

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

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

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

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

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

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

A.1.6 *PILA*: Employer–Employee panel

To construct the employer–employee panel, we use data from the firms' monthly social security payments reports between January 2008 and December 2008, and data from the match between *Super-Sociedades* and *PILA*. To move from the monthly reports to the annual panel, we proceed in two stages. First, we use the raw data and verify that we always follow the history of a worker that worked at least once in one of the firms in *Super-Sociedades*. We drop observations that have a daily wage[7] below half of the minimum daily wage. In Colombia, in contrast with the United States, workers cannot be hired hourly. Instead, they can have full-time contracts—48 hours per week—or part-time contracts—24 hours per week. Since we do not observe the type of contract—full or part time—we drop observations that have wages below the legal minimum. Following Alvarez et al. (2018), we assign workers to a single firm per month. If a worker has more than one job per month, we assign to the firm with

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

the longest spell. If, after this, there is still more than one firm per worker, we assign the firm with the highest wage. In addition to wage, firm, and worker identifiers, and date, we store the worker's region and city, the firm's registered region and city, the four-digit ISIC codes and aggregate sectors, a dummy, and a variable of whether the worker was on maternity leave. Moreover, using information about tax brackets in Colombia, we construct net wages and total labor per worker.[8]

Finally we convert all values to real December 2018 USD by first deflating the variables by CPI to remove Colombia's inflation and then using the average COP–USD exchange rate of December 2018, 3,208.263.[9] This avoids including exchange-rate fluctuations in the analysis and US price adjustments.[10]

In the second stage, we move from monthly to annual frequency using two different approaches. First, we use only information for December each year. With this method, we observe year-to-year changes that coincide with the date of the financial reports. Our main specifications use this version. As a robustness check, we aggregate using data from all months and generate monthly averages, following Alvarez et al. (2018). That is, if a worker has more than one job per year, we assign the firm with the longest spell. If, after this, we still have more than one firm per worker, we assign the firm with the highest wage. After using any of the previous alternatives, we construct growth rates of wages, labor costs, and net wages to define

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

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

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

job-market transitions. First, we define duration of unemployment as the number of periods that the worker was absent from the database. It is important to recall that being absent on the database does not mean that the worker was unemployed. The worker could have been either unemployed or working in the informal sector. We call this unemployment for simplicity. Second, we define employment status on the previous period. A worker can remain employed (EE) or move from unemployment to employment (UE). Third, we define whether a worker is an entrant to the firm. For this status, we use two alternative measures. The first indicates if a worker started working in the firm in the current period. The second measure of the status tells us that a worker is an entrant if the number of years worked on the firm is below the average number of years worked. In this same, sense we define tenure as the number of years a person has been with a firm. It is important to notice that our measure of tenure is limited by the number of years in the data, 2008–2018. Finally, we define if a worker was rehired by a firm. That is, the worker previously worked in the firm, was hired by another firm for at least one period or absent from the data and then returned to the firm. After measuring the labor-market transitions, we add gender and age to our data. We use an additional appendix of the original *PILA* that includes the individual identifier *personabasicaid*, gender, and date of birth. At this point, we restrict our sample to workers aged between 18 and 60 years in 2008 because 18 is the minimum legal working age in Colombia and 60 is the legal retirement age for males.[11] However, we want to observe the cohort that turned 60 in 2008 until the end of the sample.[12]

[11] It is 58 for women.

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

A.1.7 *PILA*: Firms panel

We create a firms panel about the firms' labor force using the annual version of the workers in *PILA*. Basically, we aggregate the workers' information per firm *id*. We aggregate per date and per date and type of worker: incumbents and entrants. We first create variables containing information about employment and generate total employment of the firm as the total number of workers, entrants, and incumbents. To measure the importance of entrants in the firm, we construct three variables: tenure as the average duration of employment, the proportion of entrants to employment, and entrants to incumbents. Then we move to a block of variables measuring the payroll of the firm. Our main variables are wage bill as the sum of all wages, average wage, standard deviation of log wages, and the 10th, 50th and 90th percentiles of wages per firm to measure changes in the distribution. We create a third block of variables containing demographic characteristics of the workers: age and gender. Since our goal is to measure changes in employment, wages, and ages, we generate for each variable its corresponding version in logs and their log changes. Finally, we construct a block containing firm geographic and sectoral information. We construct a measure of the broad sector using information on the section letter of the ISIC Revision 4 code in the first year that we observe the firm. We define 20 broad sectors following the international standard classification.[13] We create the number of locations, as the total number of different cities that workers report as their city of employment.

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

A.2 Appendix: Empirical Results

Table A.4: Connected Set of Credit-Supply Shocks: All Firms and Banks Are Connected

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

Table A.5: Summary Statistics: Growth Rates

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

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

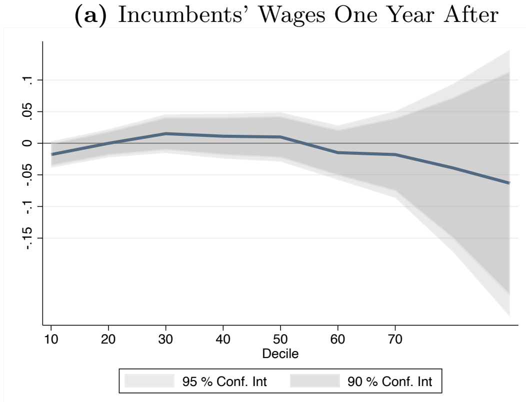
Table A.6: On Impact Effect of the Credit-Supply Shock on Banking Debt

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

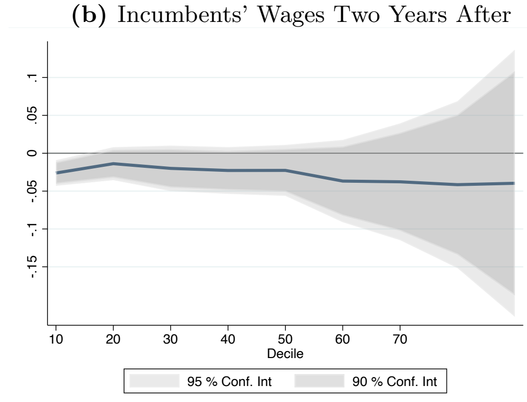
Note: Robust Standard errors in parentheses clustered at the firm and time levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimated effect on banking debt using equation (1.5) for $h = 0$. We measure banking debt from the financial reports as the ratio of banking debt to total debt.

Figure A.1: Effects on Incumbents' and Entrants' Wage Distribution One and Two Years After a Positive Credit-Supply Shock

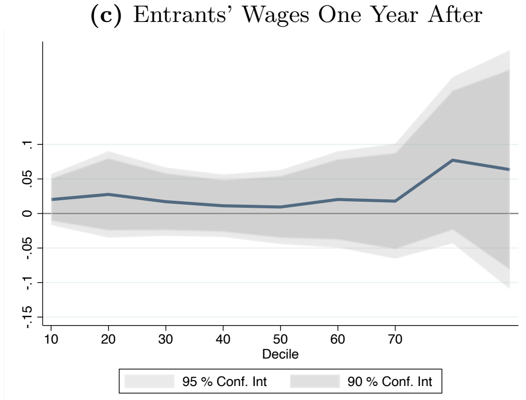
(a) Incumbents' Wages One Year After



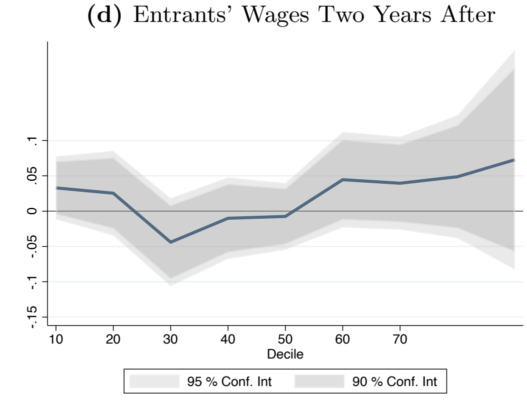
(b) Incumbents' Wages Two Years After



(c) Entrants' Wages One Year After



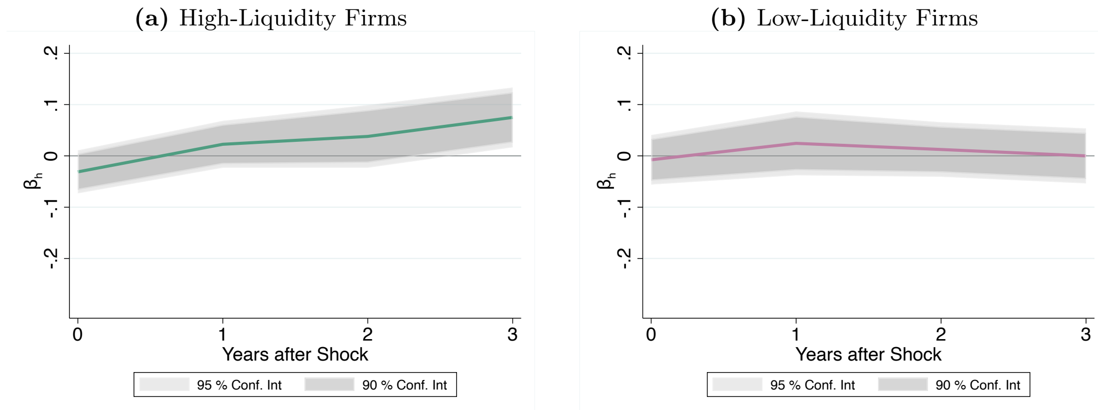
(d) Entrants' Wages Two Years After



Note: Panel **(a)** shows the estimated effect on each income decile for incumbents using equation (1.7) for $h = 1$. Panel **(b)** estimates it for $h = 2$ Panels **(c)** and **(d)** do the same for entrants. Each regression for incumbents has 1,578,695 observations for $h = 1$ and 1,003,026 for $h = 2$. Each regression for entrants has 453,462 observations for $h = 1$ and 292,513 for $h = 2$. We report 90% and 95% confidence intervals of robust standard errors clustered at the individual and time levels.

A.2.1 Liquidity

Figure A.2: Impulse-Response Functions of Average Wages for High- and Low-Liquidity Firms



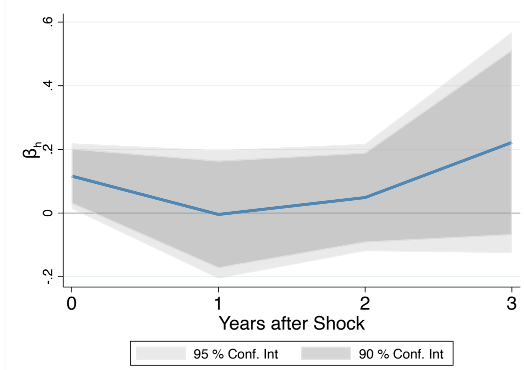
Note: Panel **(a)** shows the estimated effect on average wages using equation (1.5) for high-liquidity firms. Panel **(b)** shows the estimated effect on average wages using equation (1.5) for low-liquidity firms. A high-liquidity firm is a firm with average cash and short-term investment to assets ratio above the median. We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

Figure A.2 shows the effect on average wages. The effect is positive and sizable for high-liquidity firms two years after the shock. For a firm with a positive credit-supply shock of one standard deviation, average wages are 1.3% higher three years after the shock. This result is consistent with the expansion of working capital two years after the shock for high-liquidity firms in Figure 1.7a. We find no evidence of an effect for low-liquidity firms.

A.2.2 Additional results

Large shocks

Figure A.3: Large Shocks Increase Employment on Impact: Reconciling Our Results With Financial Crises Results in Developed Economies



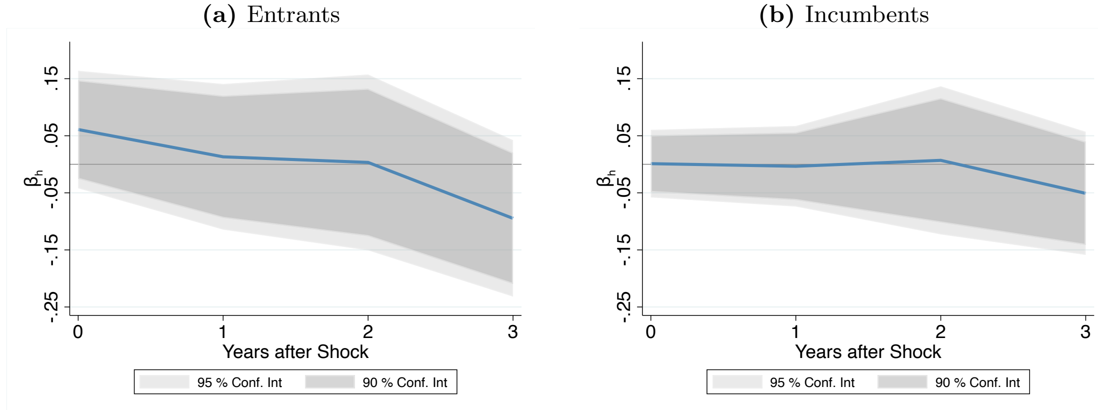
Note: Robust standard errors clustered at the firm and time levels. All specifications include as controls lagged log sales, cash, log of number of locations, and demeaned leverage. Sample sizes: $h = 0$: 23,125, $h = 1$: 16,609, $h = 2$: 12,688, $h = 3$: 10,130.

Incumbents and entrants

We split our sample between incumbents and entrants. We estimate the effect on employment using equation (1.5) for each group. Figure A.4 shows no differences in the number of entrants compared to incumbents. A compositional effect should imply an increase in the number of entrants and a decline in the number of incumbents. Also, we repeat the exercise on each wage decile using equation (1.7). Figure A.1 earlier shows these results. We recompute the distribution of wages for each group. In the presence of a distributional effect, we would expect differentiated responses in terms of wages for at least one of the two distributions. We find no such different effects between these types of workers.

Figure A.4: Impulse-Response Functions of Employment for Incumbents and Entrants

(a) Entrants **(b)** Incumbents



Note: Panel **(a)** shows the estimated effect on entrants' employment using equation (1.5). Panel **(b)** shows the estimated effect on incumbents' employment using equation (1.5). We report 90% and 95% confidence intervals of robust standard errors clustered at the firm and time levels.

A.3 Appendix: Model

A.3.1 Wages

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

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

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

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

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

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

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

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

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

$$J_n(s, k, d, m, l_\text{z}, l_\text{u}) = MPL_n - w_n(1 + \theta(r^m - 1) + \lambda_{f1}) + \frac{\zeta_n(1 - \rho_n)}{q(\theta_n)}$$

$$\mathbb{E}M(s')J_n(s', k', d', m', l'_\text{z}, l'_\text{u}) = \frac{\zeta_n}{q(\theta_n)}$$

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

$$MPL_\text{u} = \frac{(1 - \mu)(1 - \mu_r) f(k, l_\text{u}, l_\text{z})^{1-\eta}}{l_\text{u}^{1-\eta_r}(\mu k^\eta + (1 - \mu)l_\text{u}^\eta)^{1-\frac{\eta}{\eta_r}}}$$

$$MPL_\text{z} = \left(\frac{f(k, l_\text{u}, l_\text{z})}{l_\text{z}}\right)^{1-\eta}.$$

The solution of the Nash bargaining problem is then

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

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

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

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

A.3.2 Calibration

Table A.7: Summary Statistics: Credit Supply Shock

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

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

Table A.8: Summary Statistics: Interest-Rate Calibration

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

Table A.9: 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

A.3.3 Results

Figure A.5: Impulse-Response Function of the Credit-Supply Shock

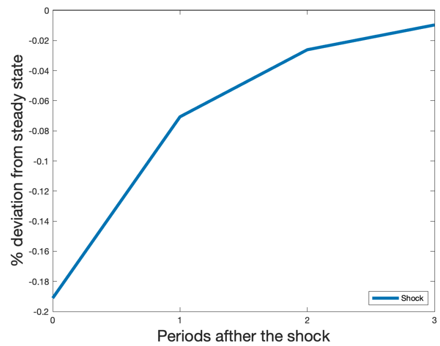
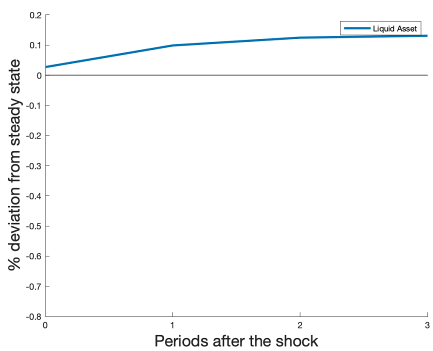
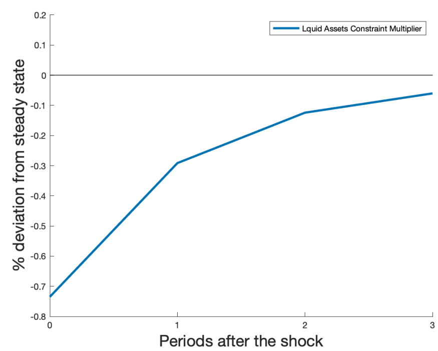


Figure A.6: Impulse-Response Functions for Liquid-Asset Holdings and Borrowing Interest Rate to a Positive Credit-Supply Shock

(a) Liquid Assets



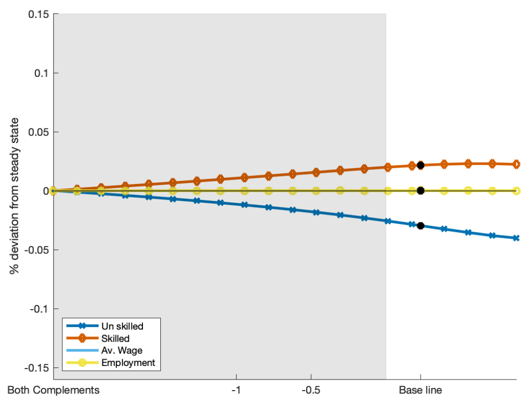
(b) Borrowing Interest Rate



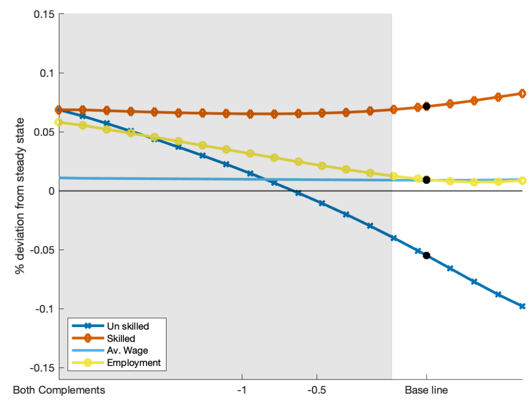
Note: Impulse-response functions for the baseline model simulations.

Figure A.7: Sensitivity Analysis of the Labor-Market Outcomes to the Substitution Parameter Between Capital and Low-Skilled Workers η_r

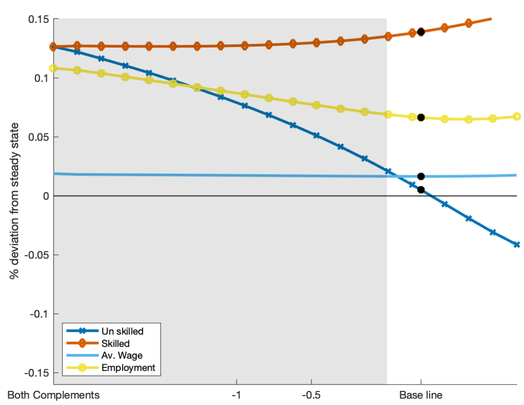
(a) $h = 0$



(b) $h = 1$



(c) $h = 2$



(d) $h = 3$

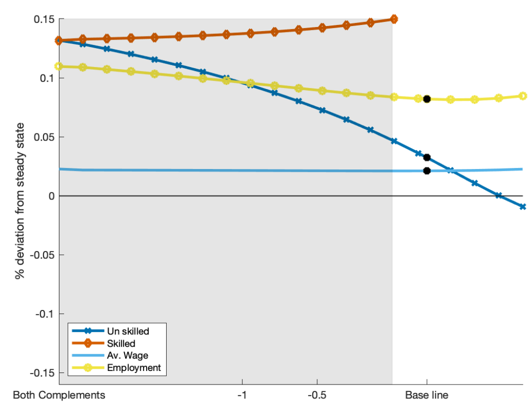
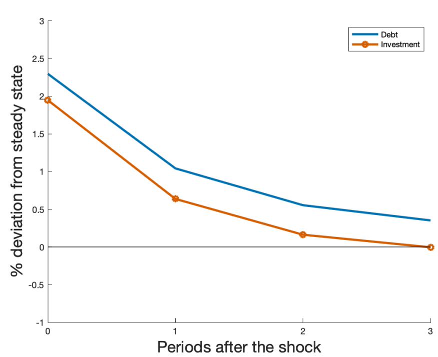
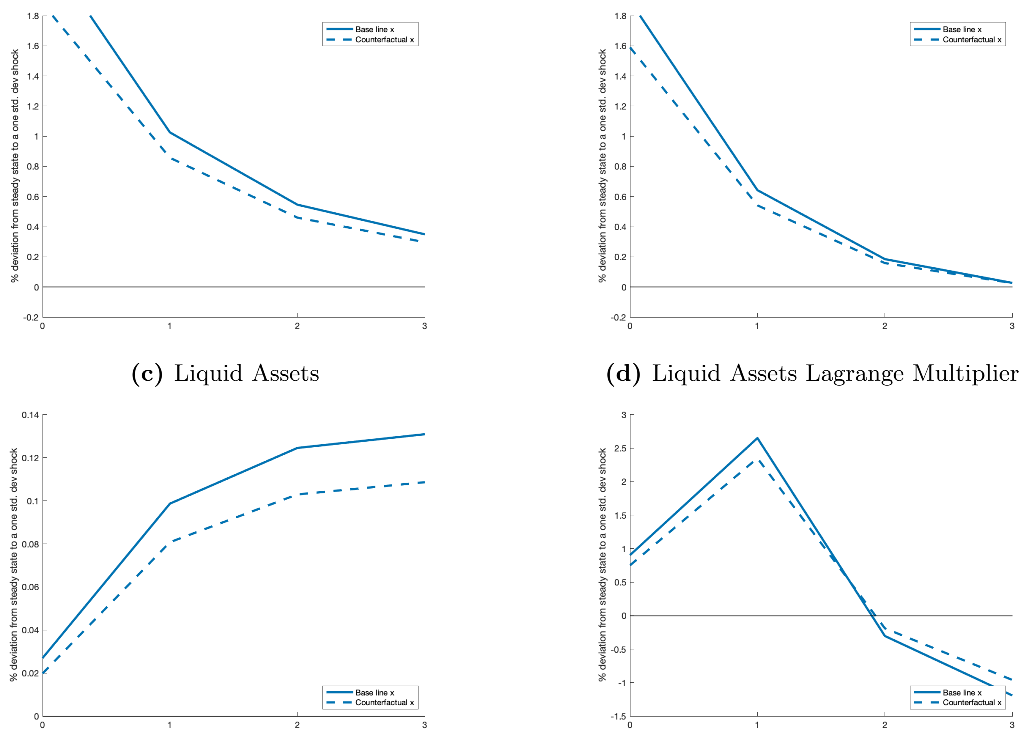


Figure A.8: Impulse-Response Functions of Unconstrained Firms' Debt and Capital to the Credit-Supply Shock



A.3.4 Counterfactual

Figure A.9: Comparing the Impulse-Response Functions on Debt, Investment, and Liquid Assets to a Positive Credit-Supply Shock for Different Levels of $\bar{\tau}$



(a) Debt **(b)** Investment

(c) Liquid Assets **(d)** Liquid Assets Lagrange Multiplier

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

APPENDIX B

Appendices to Chapter 2

B.1 Appendix: Data

Using data from PWT 9.1, we aggregate real GDP in PPP constant dollars , GDP in nominal dollars, population, and total investment in nominal dollars, into blocks A and B, as the sum of the country level values n in block i and year t.[1] Using these values, we compute real GDP in PPP *per capita* and the investment ratio, per block as the ratio of the aggregated GDP PPP to population, and total investment to GDP in nominal US, correspondingly.[2]

Using data from WDI, we aggregate sectoral shares as the average sectoral share per year within a block. The reason to use a different aggregation method is because before 1980, there are substantial missing values in the cross-section, and the first method would result in an under estimation. Table 2.1 shows the summary statistics for the main variables of our analysis.

[1] Block level variables are defined as $X_{i,t} = \sum_{n=1}^{N} x_{i,n,t}$

[2] Block level ratios are defined $\frac{X_{i,t}}{Y_{i,t}} = \frac{\sum_{n=1}^{N} x_{i,n,t}}{\sum_{n=1}^{N} y_{i,n,t}}$

Table B.1: Summary Statistics

	Mean	**Std. Dev**	**Min**	**Max**	**T**
GDP PC in PPP	28400.01	10881.53	11452.16	47523.39	58
Investment to GDP	24.09	1.99	19.54	27.81	58
Agriculture to GDP	4.37	2.36	1.65	10.55	58
Manufacturing to GDP	27.26	2.73	22.25	30.70	58
Services-GDP to GDP	59.90	4.53	53.72	66.64	48

B.2 Appendix: Trade by sector

Figure B.1: All Countries in Blocks A and B

(a) Exports **(b)** Imports

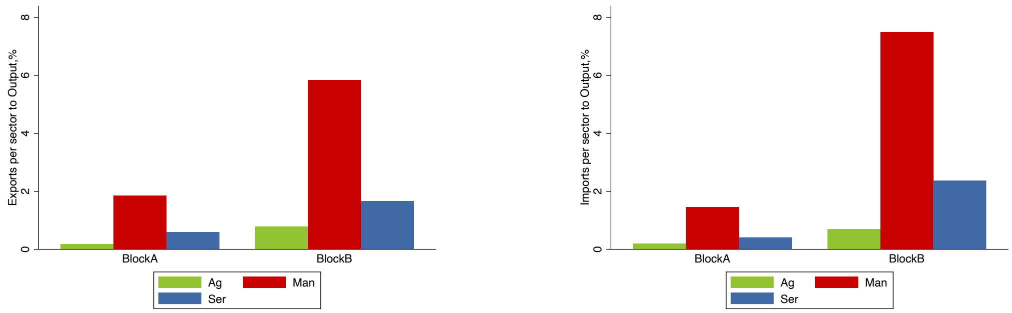
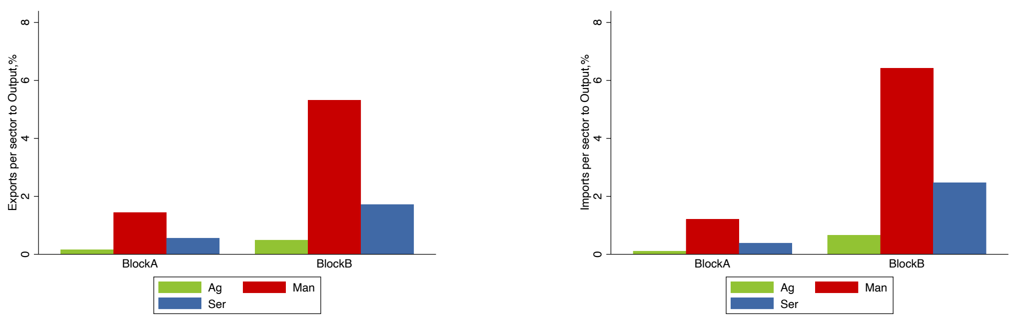


Figure B.2: Excluding Mexico

(a) Exports **(b)** Imports



Note: We use data from the WIOD input output tables from 2000-2014. Agriculture corresponds to ISIC divisions 1-5. Manufacturing corresponds to ISIC divisions 10-45. Services correspond to ISIC divisions 50-99. Each bar in Panels A and C represents the average exports per sector to total output in Blocks A and B between 2000-2014. Each bar in Panels B and S represents the average exports per sector to total output in Blocks A and B between 2000-2014.

B.3 Appendix: Calibration

B.3.1 Labor Shares

Table B.2: Summary Statistics: Capital Shares per Country of Block A over years 2000-2014

	Agriculture, θ	**Manufacturing, γ**	**Services, φ**
AUS	.7	.3	.4
AUT	.1	.4	.4
BEL	.5	.4	.4
CAN	.8	.4	.4
CHE	.3	.4	.4
DEU	.2	.3	.4
DNK	.7	.3	.3
FIN	.3	.4	.4
FRA	.4	.3	.4
GBR	.7	.2	.3
ITA	.5	.3	.5
JPN	.5	.3	.4
LUX	.2	.3	.5
NLD	.8	.4	.4
NOR	.9	.3	.4
SWE	.4	.5	.4
USA	.7	.4	.4

B.3.2 TFP Growth

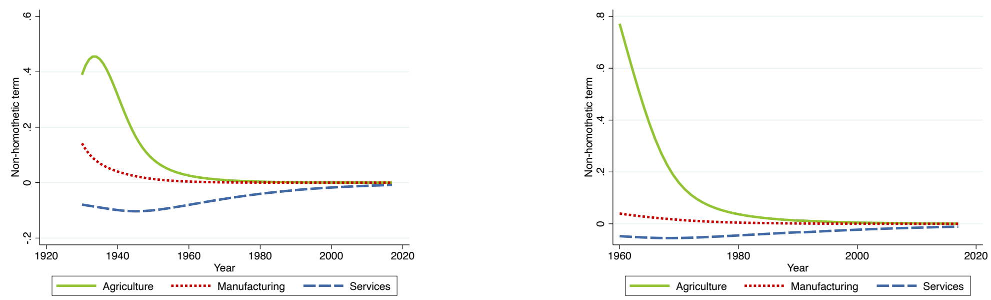
Table B.3: Summary Statistics: TFP Growth Rates per Country of Block A over years 2000-2014

	Agriculture, θ	**Manufacturing, γ**	**Services, φ**
AUS	.97	1.03	1.01
AUT	.93	1	1.01
BEL	1.04	1.02	1.02
CAN	1	1.05	.99
CHE	.98	1	.99
DEU	.98	.99	1
DNK	1.02	1.01	1.02
FIN	.96	1.07	1.02
FRA	1.07	1.04	1.02
GBR	1.06	1.05	1
ITA	1	1.04	1
JPN	1.1	1.02	.96
LUX	.99	1.05	1.03
NLD	.98	1	1.01
NOR	1.02	1.02	1.02
SWE	.98	1.05	1.02
USA	.96	.96	1

B.3.3 Simulated path of the non-homothetic term

Figure B.3: The simulated paths of the non-homothetic term for both Blocks A and B

(a) Block A **(b)** Block B

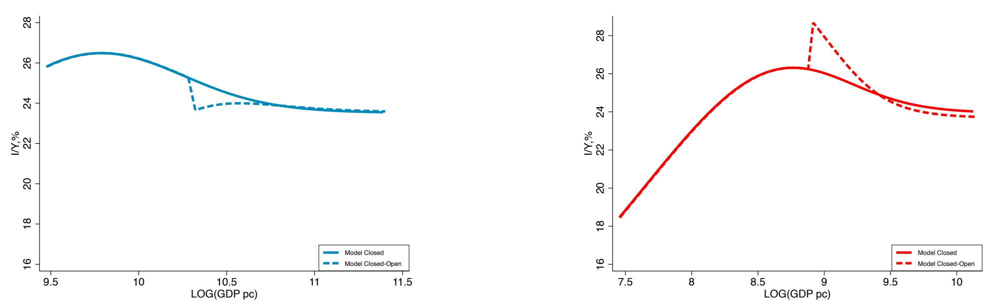


Note: Each line represents the simulated path of the non-homothetic term implied by the model. Recall that the non-homothetic term is equal to $\frac{\epsilon^i_{jt}}{g^i_{jt}} C^i_{jt}$, where $\epsilon^i_{jt} = \rho_j \epsilon^i_{jt-1}$

B.4 Appendix: Comparing the Model to the Data

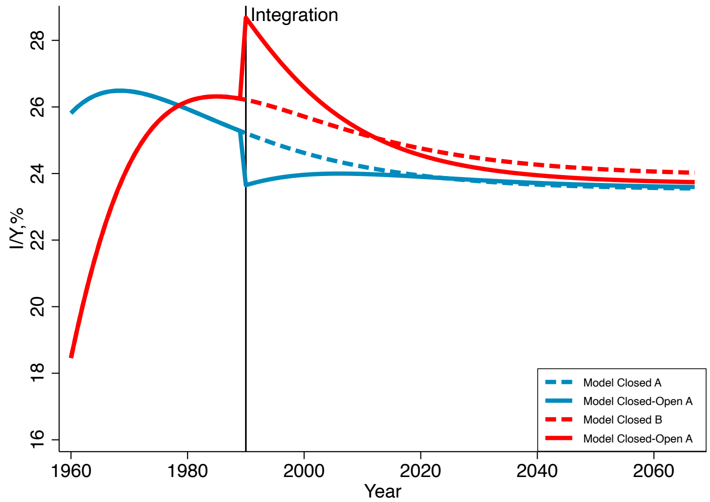
Figure B.4: The simulated paths of the investment rate relative to real per capita GDP for both Blocks A and B, 1960-2067

(a) Block A **(b)** Block B



Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The solid line corresponds to the simulated results of the closed economy, and the dashed line corresponds to the open economy opening in 1991.

Figure B.5: The simulated paths of the investment rate relative to time for both Blocks A and B,1960-2067



Note: Each dot corresponds to an observation in Block j in year t. Data Source: PWT9.1. The solid line corresponds to the simulated results of the closed economy, and the dashed line corresponds to the open economy opening in 1991.

Figure B.6a: Determinants of the structural transformation process: Block A

(a) Baseline **(b)** Growth rates **(c)** Labor shares **(d)** Efficiency **(e)** Preferences

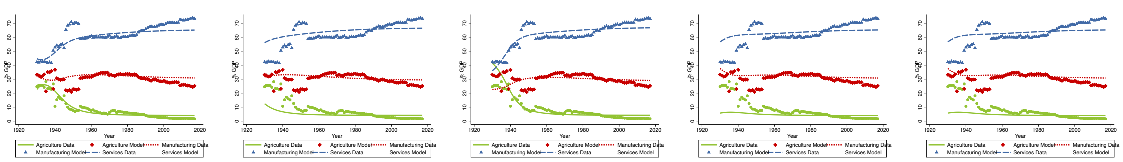
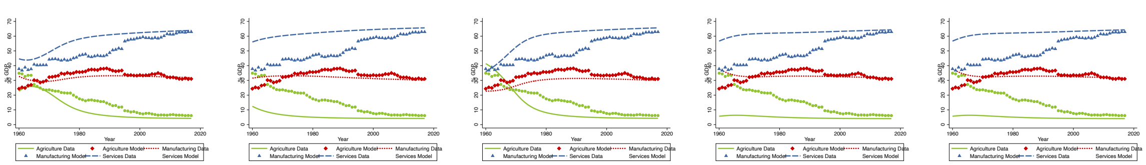


Figure B.6b: Determinants of the structural transformation process: Block B

(a) Baseline **(b)** Growth rates **(c)** Labor shares **(d)** Efficiency **(e)** Preferences



Note: Panel (a) compares the simulated path of the investment share to GDP versus of the baseline model. Panel (b) uses the same growth rate across sectors and regions. We set $\lambda = \mu = \nu = 1.01$. Panel (c) the same labor share across sectors and regions $\theta = \gamma = \varphi = 0.38$. Panel (d) uses the same efficiency parameters across sectors by region: $A^A = B^A = C^A = 0.48$, and $A^B = B^B = C^B = 0.24$. Panel (d) uses Cobb-Douglas preferences. We set $\epsilon^i_{j,0} = 0$ and $\rho_j = 0$.

APPENDIX C

Appendices to Chapter 3

C.1 Appendix: Summary Statistics

Table C.1: Summary Statistics

	Mean	**Std. Dev**	**Pctile 90**	**Pctile. 5**	$\mathbb{N}$
			Controls		
Hours$^{\triangleleft}$	39.41	1.27	41.40	37.49	1180
Weeks$^{\triangleright}$	47.01	0.99	48.41	45.27	1180
Employment Share	0.96	0.02	0.98	0.92	1180
$> 40 weeks$ per year share$^{\circ}$	0.86	0.03	0.90	0.81	1180
$> 50 weeks$ per year share$^{\circ}$	0.76	0.05	0.83	0.68	1180
Share of Manufacturing*	0.18	0.06	0.29	0.10	1180
Share of Transportation ad Communication*	0.07	0.02	0.10	0.04	1180
Share of Whole Sales*	0.03	0.01	0.05	0.01	1180
Share of Retail Sales*	0.17	0.03	0.22	0.14	1180
Share of Professional Services*	0.30	0.05	0.39	0.23	1180
Share of Public Administration*	0.05	0.03	0.11	0.02	1180
Share of Other Services*	0.10	0.03	0.14	0.06	1180
Share of Financial Sector*	0.06	0.03	0.11	0.03	1180
Share of Agriculture and Mining*	0.03	0.04	0.11	0.01	1180
White$^{\diamond}$	0.80	0.14	0.96	0.54	1180
Share Home owners	0.73	0.10	0.86	0.55	1180
Share Urban Population	0.85	0.13	1.00	0.60	267

Note: All variables are the average of ACS respondends per county
$^{\triangleleft}$ Average number of hours worked per week
$^{\triangleright}$ Average number of weeks worked per year
$^{\circ}$ Share of respondents who report working more than 40 and 50 weeks per year, correspondingly
* Share of workers in each 1990 Census Industry Codes main categories
$^{\diamond}$ Share of respondents who identify as White

Table C.2: Summary Statistics More Inequality and Income Deciles

	Mean	**Std. Dev**	**Pctile 90**	**Pctile. 5**	$\mathbb{N}$
		Inequality and Income			
80th Pctile$^{\diamond}$	1330.69	292.38	1914.53	995.02	1180
70th Pctile$^{\diamond}$	1070.63	226.42	1508.99	826.06	1180
60th Pctile$^{\diamond}$	880.67	177.85	1239.15	660.88	1180
40th Pctile$^{\diamond}$	599.70	114.80	826.10	452.70	1180
30th Pctile$^{\diamond}$	477.29	89.21	638.18	360.46	1180
20th Pctile$^{\diamond}$	355.26	65.55	468.67	258.96	1180
R90-80*	1.35	0.07	1.48	1.24	1180
R90-70*	1.68	0.13	1.90	1.50	1180
R90-60*	2.04	0.19	2.37	1.77	1180
R90-40*	3.00	0.37	3.63	2.48	1180
R90-30*	3.77	0.54	4.72	3.01	1180
R90-20*	5.09	0.87	6.67	3.90	1180
R50-40*	1.22	0.05	1.30	1.15	1180
R50-30*	1.53	0.10	1.71	1.39	1180
R50-20*	2.07	0.22	2.49	1.75	1180
		% Change Inequality and Income Peak-Trough			
80th Pctile	-0.01	0.05	0.08	-0.10	375
70th Pctile	-0.01	0.05	0.08	-0.09	375
60th Pctile	-0.02	0.06	0.08	-0.12	375
40th Pctile	-0.04	0.07	0.08	-0.14	375

Table C.2: Summary Statistics More Inequality and Income Deciles

	Mean	Std. Dev	Pctile 90	Pctile. 5	$\mathbb{N}$
30th Pctile	-0.06	0.08	0.07	-0.18	375
20th Pctile	-0.08	0.09	0.06	-0.24	375
R90-80	-0.00	0.05	0.07	-0.10	375
R90-70	-0.00	0.06	0.09	-0.11	375
R90-60	0.01	0.07	0.11	-0.10	375
R90-40	0.02	0.08	0.13	-0.11	375
R90-30	0.04	0.08	0.19	-0.10	375
R90-20	0.06	0.10	0.23	-0.11	375
R50-40	0.01	0.04	0.08	-0.05	375
R50-30	0.03	0.06	0.12	-0.06	375
R50-20	0.06	0.08	0.20	-0.07	375

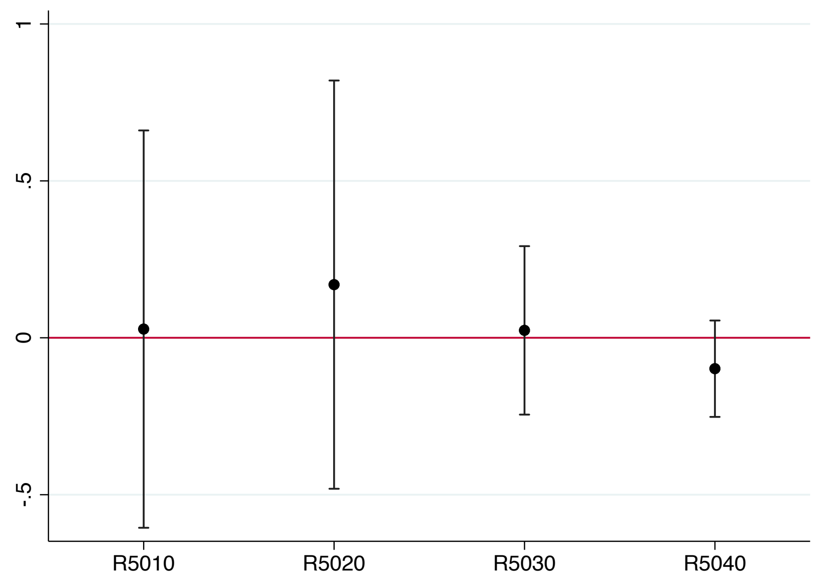
Table C.2: Summary Statistics More Inequality and Income Deciles

	Mean	**Std. Dev**	**Pctile 90**	**Pctile. 5**	$\mathbb{N}$
	Change Inequality and Income Peak-Recovery				
R90-80	0.01	0.06	0.10	-0.09	331
R90-70	0.02	0.07	0.13	-0.08	331
R90-60	0.03	0.08	0.17	-0.09	331
R90-40	0.06	0.09	0.20	-0.08	331
R90-30	0.09	0.10	0.23	-0.07	331
R90-20	0.11	0.11	0.30	-0.09	331
R50-40	0.02	0.04	0.08	-0.04	331
R50-30	0.04	0.06	0.15	-0.06	331
R50-20	0.07	0.08	0.21	-0.06	331
80th Pctile	-0.01	0.07	0.12	-0.12	331
70th Pctile	-0.03	0.07	0.10	-0.14	331
60th Pctile	-0.04	0.08	0.10	-0.16	331
40th Pctile	-0.07	0.08	0.07	-0.20	331
30th Pctile	-0.09	0.09	0.07	-0.26	331
20th Pctile	-0.12	0.10	0.07	-0.29	331

$^{\diamond}$ U.S 2012 Dollars deflated with the PCE deflator
* Ratio of income deciles using equation 3.2

C.2 Appendix: Additional Results Changes in Income Inequality Peak-Trough

Figure C.1: Effect of Financial Crisis Across the Distribution of Income

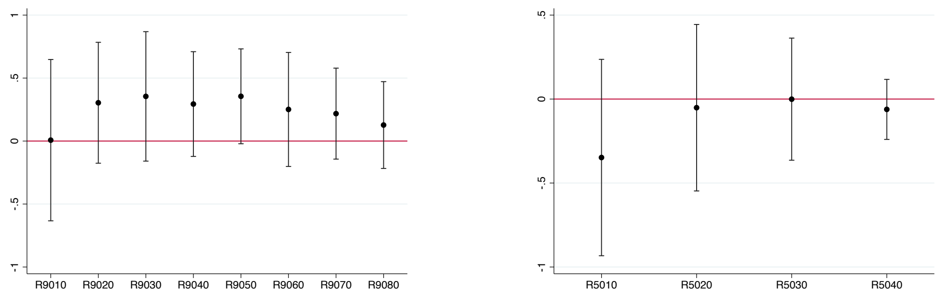


Note: The vertical axis shows the estimated coefficients of equation 3.5 for different deciles ratios during the peak and trough and their corresponding confidence intervals at a 95% significance level. The horizontal axis shows the each decile ratio. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level

C.3 Appendix: Additional Results Changes in Income Inequality Peak-Recovery

Figure C.2: Effect of Financial Crisis Across the Distribution of Income

(a) Top of the Distribution **(b)** Bottom of the Distribution



Note: The vertical axis shows the estimated coefficients of equation 3.6 for different deciles ratios during the peak and recovery and their corresponding confidence intervals at a 95% significance level. The horizontal axis shows the each decile ratio. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level

Table C.3: Robustness: Effect of Financial Crises on Labor Income Inequality on the Recovery

	(1)	(2)	(3)	(4)	(5)
	$\Delta_{07-15}I_{9050}$	$\Delta_{07-15}I_{9050_D}$	$\Delta_{07-15}I_{9050_A}$	$\Delta_{07-15}I_{9050_L}$	$\Delta_{07-15}I_{9050_{F3}}$
Δ HH Net Worth	0.51597^{**}	0.51597^{**}	0.51597^{**}	0.28231^{*}	0.71204^{**}
	(0.201)	(0.201)	(0.201)	(0.163)	(0.299)
N	240	240	240	240	

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-15}I_{9050}$, on Changes in Housing Net Worth, Δ HH Net Worth using using using equation 3.6. Column 1 reports the benchmark result. Column 2 uses $R90-50$ with State Level GDP deflator as dependent variable. Column 3 uses $R90-50$ with IPUMS Adjust factor as dependent variable. Column 4 uses linearly de-trended $R90-50$. Column 5 uses linearly de-trended, IPUMS Adjust factor and State level GDP deflator $R90-50$ as dependent variable. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Additional Results Deciles and Compositional effect

Table C.4: Changes in Employment Peak-Trough

Dependent Variable: Change in Total Employment			
	(1)	(2)	(3)
	$\Delta_{07-09}E$	$\Delta_{07-09}E_{90}$	$\Delta_{07-09}E_{50}$
Δ HH Net Worth	0.04625	0.02522	0.07113
	(0.037)	(0.051)	(0.052)
N	240	240	240
Controls	Yes	Yes	Yes

Note: This table reports changes on employment,$\Delta_{07-09}E$ and $\Delta_{07-15}E$, on Changes in Housing Net Worth, Δ HH Net Worth using using using equation 3.6. Column 1 reports changes in overall employment, column 2 reports changes in employment for workers on th 90th percentile, and column 3 reports changes in employment for the 50th percentile. An individual is classified in the 90th percentile if $w_{80} < w_i \leq w_{90}$. An individual is classified in the 50th percentile if $w_{40} < w_i \leq w_{50}$. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

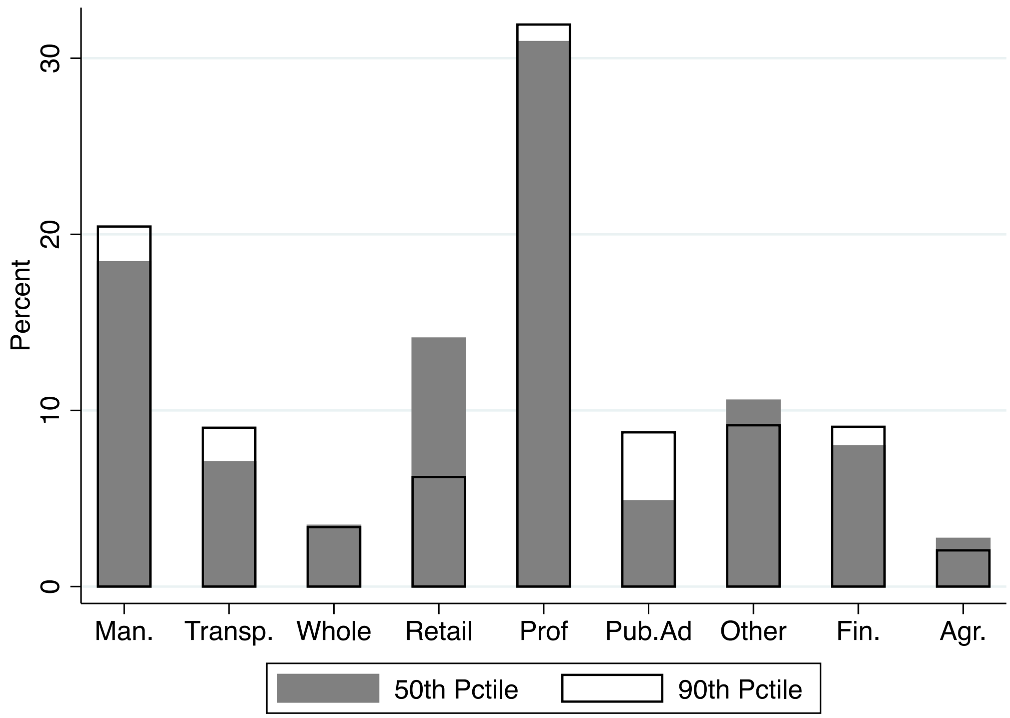
Table C.5: Compositional Effect: Changes in Income and Employment Peak-Recovery

	(1)	(2)	(3)
	A. Full Sample		
	$\Delta_{07-15}I_{9050}$	$\Delta_{07-15}W_{90}$	$\Delta_{07-15}W_{50}$
Δ HH Net Worth	0.38424^{**}	0.09599	-0.28825^{**}
	(0.150)	(0.197)	(0.140)
	C. Only workers with $weeks > 50$**,** F		
	$\Delta_{07-15}I_{9050_{F2}}$	$\Delta_{07-15}W_{90_{F2}}$	$\Delta_{07-15}W_{50_{F2}}$
Δ HH Net Worth	0.53452^{**}	0.27370	-0.26083^{*}
	(0.228)	(0.227)	(0.153)
N	240	240	240

Note: This table reports different specifications of changes of R90-50,$\Delta_{07-15}I_{9050}$, column 1 of panels A and B, on Changes in Housing Net Worth, Δ HH Net Worth using using equation 3.5. Columns 2 and 3, report changes on the 90th,W_{90} and 50th, W_{50} percentiles using equation 3.5. Panel A reports results using all workers from the sample. Panel B reports results with workers that reported more than 50 weeks per year, $F2$. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

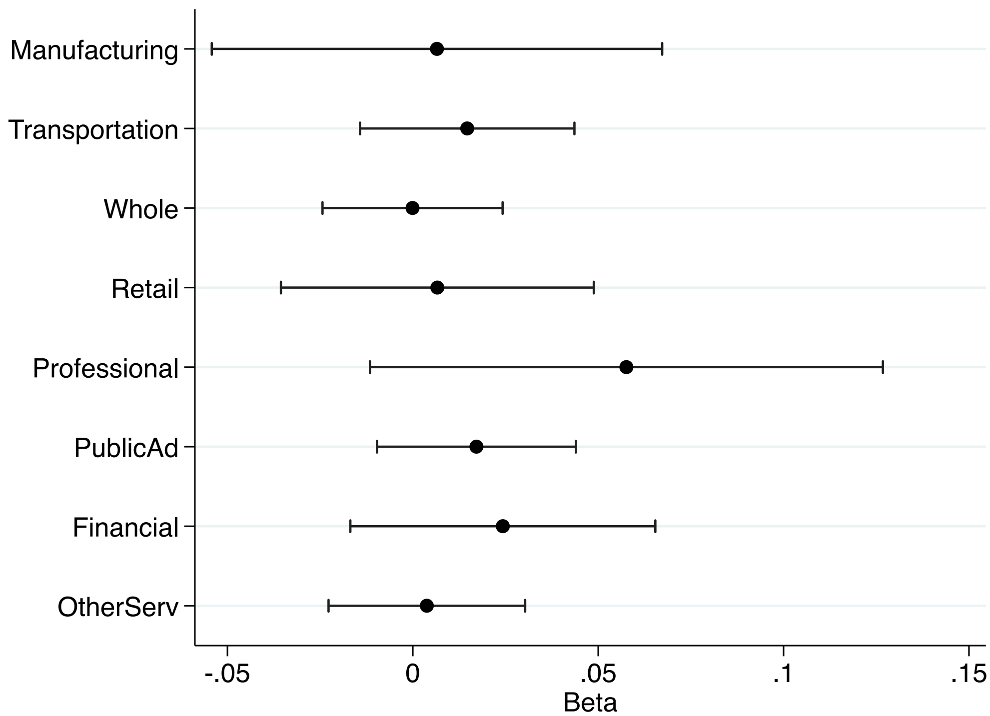
C.5 Appendix: Additional Within and Between Industries Inequality

Figure C.3: Industry Shares



Note: This graphs shows the percentage of workers during years 2007, 2009, and 2015 in each industry and percentile, 50th and 90th correspondingly.. I classify the sample in 9 industries according to 1990 Census Industry Codes main categories. From left to right: Manufacturing, Transportation & Communication, Whole Sales, Retail Sales, Professional Services, Public Administration, Other Services, Financial Sector, and Agriculture and Mining. A worker belongs to the 50th percentile $w_{40} < w_i \leq w_{50}$, and a worker belongs to the 90th percentile if $w_{80} < w_i \leq w_{90}$

Figure C.4: Within Industries Inequality Peak-Recovery



Note: The horizontal axis shows the estimated coefficients of each term, industry, of the Within inequality in equations 3.7 , 3.8, and their corresponding confidence intervals at a 95% significance level. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level. I classify the sample in 9 industries according to 1990 Census Industry Codes main categories. From top to bottom: Manufacturing, Transportation & Communication, Whole Sales, Retail Sales, Professional Services, Public Administration, Other Services, Financial Sector, and Agriculture and Mining. A worker belongs to the 50th percentile $w_{40} < w_i \leq w_{50}$, and a worker belongs to the 90th percentile if $w_{80} < w_i \leq w_{90}$

C.6 Appendix: Additional Within and Between Occupations Inequality

Table C.6: Within Occupation-Skill Variation by Percentiles

	(1)	(2)	(3)	(4)	(5)	(6)
			A. Peak-Trough			
	$\Delta_{07-09}Wt_S$	$\Delta_{07-09}Wt_{S,90}$	$\Delta_{07-09}Wt_{S,50}$	$\Delta_{07-09}Wt_U$	$\Delta_{07-09}Wt_{U,90}$	$\Delta_{07-09}Wt_{U,50}$
HH Net Worth	0.20992*	0.19207**	0.01785	0.22486*	0.18515**	0.02992
	(0.111)	(0.093)	(0.024)	(0.120)	(0.084)	(0.047)
N	267	267	267	264	264	267
			A. Peak-Recovery			
	$\Delta_{07-15}Wt_S$	$\Delta_{07-15}Wt_{S,90}$	$\Delta_{07-15}Wt_{S,50}$	$\Delta_{07-15}Wt_U$	$\Delta_{07-15}Wt_{U,90}$	$\Delta_{15-15}Wt_{U,50}$
HH Net Worth	-0.04305	0.03491	-0.07796*	-0.03556	0.02108	-0.08495
	(0.177)	(0.144)	(0.045)	(0.196)	(0.136)	(0.069)
N	240	240	240	238	238	240

Note: This table estimates equation the Within components of equation 3.10. $\bar{W}_S$ is average change in High-Skill Occupations, and $\bar{W}_U$ is average change in the Low-Skill Occupations. I classify the sample in occupations according to the SOC 2010 classification. Where High-Skill Occupations are Management, Professional, and Related Occupations (major groups 11-29), Service Occupations (major groups 31-39) , Sales and Office Occupations (major groups 41-43); and Low-Skill occupations are Natural Resources, Construction, and Maintenance Occupations (major groups 45-49), and Production, Transportation, and Material Moving Occupations (major groups 51-53). For further details on the classification, see `https://www.bls.gov/soc/soc_2010_user_guide.pdf`. All results include as controls, race, urban, homeowners, schooling and industry shares. Standard errors in parentheses are clustered at the state level, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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