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Abstract

We propose a novel channel through which rising income inequality affects job creation and macroeconomic outcomes. High-income households save relatively more in stocks and bonds but less in bank deposits. A rising top income share thereby increases the relative financing cost for bank-dependent firms, which in turn create fewer jobs. Exploiting variation in top income shares across US states and an instrumental variable strategy, we provide evidence for this channel. We then build a general equilibrium macro model with heterogeneous households and heterogeneous firms and calibrate it to our empirical estimates. The model shows that the secular rise in top incomes accounts for 13 percent of the decline in the employment share of small firms since 1980. Through the new channel, rising inequality also reduces the labor share and aggregate output. Model experiments show that ignoring the link between inequality and job creation understates welfare effects of income redistribution.

Key words: income inequality, household heterogeneity, bank lending, job creation, business dynamism

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1 Introduction

The rise in income inequality over the past decades has given new impetus to the long-standing debate on its effects on the real economy (Jones, 2015). Recent work shows that rising top income shares can depress aggregate demand and output, as high-income households save a larger fraction of their income (Auclert and Rognlie, 2017, 2020) and finance the indebtedness of lower-income households (Mian, Straub and Sufi, 2020, 2021a). This paper proposes a novel channel linking income inequality to job creation and economic activity through firms' financing conditions.

The channel rests on two observations. First, low-income households hold a larger share of their financial wealth in the form of bank deposits, while top earners invest in financial assets such as stocks or bonds. Second, banks' access to deposits affects their cost of funds and ability to grant loans, and changes in loan supply affect bank-dependent firms. These observations suggest that rising top income shares, through non-homotheticity in the allocation of savings, improve funding conditions for firms with access to bond and equity financing. But they lead to a relative increase in financing costs for bank-dependent firms, which in turn create relatively fewer jobs than firms with access to other forms of funding.

The first part of the paper tests this mechanism empirically with US data. The second part builds a quantitative macroeconomic model to study the consequences of rising top income shares for macroeconomic outcomes and welfare. Our analysis uncovers an intricate link between two salient trends in the US economy: the increase in top income shares on the one hand and the changing firm size distribution and decline in dynamism on the other.

Our empirical analysis establishes that an increase in the top 10% income share reduces job creation among bank-dependent firms and provides evidence for the mechanism. Motivated by the literature on the importance of bank lending for small firms, our baseline analysis focuses on job creation of small relative to large firms. For identification, we exploit variation in top income shares across US states from 1980 to 2015, using an instrumental variable (IV) strategy and granular fixed effects.

We find that a 10 percentage point (p.p.) increase in the top income share significantly reduces the relative net job creation rate of smaller, bank dependent firms by 1.2 p.p. The US-wide increase in the income share of the top 10% from 1980 to 2015 was around 16 p.p. Small firms' net job creation rate would be 1.9 p.p., or over 50%, higher today had top income shares remained at their 1980 levels. Rising top incomes reduce job creation both along the intensive and extensive margin, with 20% of the overall decline in the net job creation rate due to less firm entry and exit.

To address omitted variable bias and reverse causality we develop an instrumental variable. It builds on each state's 1970 top 10% income share, adjusted for its 'leave-one-out' national trend. Specifically, we exclude each respective state from the nationwide evolution in top incomes used to adjust initial income shares in that state. The predicted income shares are then used as an IV for the actual shares.[1]

To tighten identification, granular time-varying fixed effects control for observable and unobservable characteristics that could affect job creation within each state or within the same state and industry. State*time fixed effects absorb, for example, the effects of technological change or globalization in each state over time, two common explanations behind the rise in income inequality. When possible, we include state*industry*time fixed effects that absorb common trends that affect firms in different industries within each state. These include changes in industry concentration or import competition, as well as changes in demand across industries.

We provide evidence for the link between income inequality and firms' funding conditions. First, we show that the magnitude of the effect of rising top income shares on job creation is declining in firm size, consistent with the empirical evidence that smaller firms are more bank-dependent (Petersen and Rajan, 1994; Chodorow-Reich, 2014). Second, a given increase in top incomes reduces net job creation of small relative to large firms by more in industries that rely more on bank financing.

To investigate the effect of rising top incomes on deposits directly, we estimate bank-level regressions. We find that a rise in top income shares in banks' headquarters state has a significant positive effect on banks' deposit rates and a significant negative effect on the amount of deposits. The increase in prices and fall in quantities is consistent with higher inequality leading to a relative reduction in households' preference to save in deposits, which requires banks to raise deposit rates to attract funds and meet loan demand. We obtain similar results for commercial and industrial loans: higher top income shares increase loan rates but reduce loan amounts.

We address alternative explanations that could underlie the link between top incomes, funding conditions, and job creation. Rising top income shares could affect local demand if richer households demand more services (Boppart, 2014) that are predominately provided by smaller, bank-dependent firms. To preclude this channel, we exclude non-tradable industries from the sample or add state*industry fixed effects to our regressions and find similar effects. Further, controlling for the impact of house prices on small and large firms does not affect the results, suggesting that they are not explained by a collateral channel (Chaney, Sraer and Thesmar, 2012; Adelino, Schoar and Severino, 2015). The results are also robust to controlling for state-level education expenditure, implying that they do not arise from changes in

[1] In addition, we construct a shift-share instrument that leverages the fact that earnings dynamics in a small number of 4-digit NAICS industries account for most of the rise in US income inequality (Haltiwanger, Hyatt and Spletzer, 2024). This IV uses industries' beginning-of-period employment shares in each state, interacted with their nationwide employment evolution.

the provision of public goods (Braggion, Dwarkasing and Ongena, 2021).

The second part of the paper studies how rising top incomes affect macroeconomic outcomes and welfare in quantitative experiments. We build a macroeconomic model with heterogeneous households and heterogeneous firms and calibrate it to our estimates. This model, which features a general equilibrium interaction between household portfolios and employment decisions of firms that differ in their funding sources, is a distinct contribution.

On the households side, the model builds on the tradition of studying savings with incomplete markets and uninsurable income risk. Households allocate their portfolio between bank deposits and direct firm investments. Deposits yield a lower return but provide utility. Borrowing ideas from De Nardi (2004) and Straub (2019), the deposit share declines with income through non-homothetic savings behavior.

On the production side, the model features a continuum of firms that are heterogeneous in their productivity, as in Hopenhayn (1992). Moreover, firms can either be 'public' or 'private', similar to Peter (2021). Public firms receive direct investments from households without any financial frictions. Private firms cannot access the public capital market but require bank funding to cover their wage bill. They also need to pay a fixed cost to operate, which introduces an extensive and intensive margin of production. To circumvent the dependence on banks, private firms can become public subject to a cost. A competitive banking sector offers deposits to households and provides loans to private firms.

We calibrate the model to target the stylized facts and estimates from our empirical analysis. In the initial stationary equilibrium, we match income and portfolio shares of households, as well as the employment shares and relative sizes of the different firm types, to their counterparts in US data in the early 1980s. In our calibration an increase in the top 10% income share reduces the relative net job creation rate of small firms by the same magnitude as implied by our estimated coefficients, both along the extensive and intensive margin. The calibrated model also replicates several empirical facts that are not directly targeted. For instance, poorer households have a higher marginal propensity to consume and rely more on labor income than richer households.

Our quantitative experiment raises the top 10% income share from 34.5% to 50.5%, matching its evolution in the data over our 1980 to 2015 sample period. The initial share of 34.5% results from permanent labor income risk heterogeneity between households. The subsequent increase is generated by redistributing income from poorer to richer households through permanent lump-sum taxes and transfers that net out to zero. In this way the underlying source of rising top income shares in the model does not otherwise have direct macroeconomic implications.

We first examine macroeconomic outcomes and the impact across firms. With more income accruing to top earners, aggregate investments in public firms grow, while aggregate deposits fall, a consequence of non-homothetic preferences over different forms of savings. These changes in the supply of funds are reflected in returns: the return on public firm investments falls, while the deposit rate increases, as banks need to offer higher rates to attract deposits. Due to banks' zero profit condition the increase in bank funding costs raises the loan rate, in line with our empirical findings. Faced with higher loan rates, private firms find it more costly to hire and their job creation declines, compared to public firms. The decline is mainly driven by active private firms demanding less labor, but also by more private firms exiting the market or becoming public firms.

The model experiment shows that rising inequality has contributed to several important macroeconomic trends and lowered aggregate employment and output. A rise in the top 10% income share moves resources away from smaller bank-dependent firms towards larger firms. This inequality-induced reallocation of resources increases the employment share of large firms by 0.64 p.p. In the US, the employment share of firms with more than 500 employees has increased by 4.97 p.p. since 1980. Rising inequality thus explains around 13% of the overall increase in the large firm employment share. As larger firms are more capital-intensive, the rise in the top income share also leads to a fall in the labor share of 0.3 p.p., corresponding to around 7.5%–15% of its decline in the data over the same period. Moreover, since smaller firms have higher marginal products than larger firms, the rise in the top 10% income share reduces output by 0.3%.[2]

The experiment also shows that our mechanism amplifies the welfare effects of income redistribution. By design, redistribution towards the top increases welfare for the top 10% and decreases it for the bottom 90%, implying a decline in welfare for the average household. Our channel magnifies both the negative welfare effects at the bottom and the positive ones at the top. To establish this result, we benchmark the welfare consequences arising from our experiment to those in an alternative fixed portfolio share model that restricts households to save in deposits and public firm capital in constant proportions, irrespective of their income.

The amplification of the welfare effects arises from changes in different sources of income in equilibrium. First, as the top income share increases, private firms become more constrained and their employment and wages fall. Public firms increase employment and wages to a lesser extent, so average wages in the economy decline. As labor income matters disproportionately for lower-income households,

[2]The differences in marginal products across firm sizes are not an assumption but are implied by matching our empirical estimates. Due to financial constraints, private firms' marginal products can exceed those of public firms, independent of productivity levels.

their welfare declines. Second, capital income matters more at the top end of the income distribution. In response to receiving more income, richer households invest a higher share of their assets in public firms. As investments into public firms yield higher returns than deposits, richer households experience an additional increase in income and welfare beyond the initial transfer. In contrast, in the fixed portfolio share model savings keep flowing to public and private firms in the same proportion. Low-income households benefit from higher wages, while high-income households cannot shift their portfolio into high-return investments.

Finally, we demonstrate that our model can answer further questions related to income inequality and job creation. In an additional experiment, we generate rising income inequality through changes in households' income processes, model complementarities between different worker and firm types, and allow for aggregate income growth. While our main experiment abstracts from these features to isolate the quantitative implications of our channel, higher top income shares lead to a relative decline in job creation at bank-dependent firms, as well as the labor share, also in alternative environments.

Contribution to the literature. We contribute to three strands of literature. First, our paper speaks to a large empirical literature that investigates the effects of inequality on the real economy.[3] Early work uses cross-country panel data (Barro, 2000; Forbes, 2000; Banerjee and Duflo, 2003), which makes identification challenging as causality can go both ways. More recent papers use variation in inequality across US geographic areas. Bertrand and Morse (2016) and Coibion, Gorodnichenko, Kudlyak and Mondragon (2020) show that the consumption and debt levels of poorer households vary with local income inequality. Braggion, Dwarkasing and Ongena (2021) use an IV strategy to establish a negative effect of wealth inequality on entrepreneurship and the supply of public goods across metropolitan statistical areas between 2004 and 2012. Our paper provides well-identified evidence for a novel channel through which rising income inequality affects the real economy. To quantify its aggregate implications, we calibrate our macro model to the cross-regional estimates.

Second, our paper relates to work on the macroeconomic effects of income inequality arising from the inter-temporal decisions of households. Mian, Straub and Sufi (2021a) show that a higher top income share depresses aggregate demand in a general equilibrium model with non-homothetic consumption-savings behavior.

[3]While our paper analyzes the consequences of income inequality, a series of papers studies its causes (see Gordon and Dew-Becker (2008) and Cowell and Van Kerm (2015) for surveys). Demirgüç-Kunt and Levine (2009) study how financial sector policy affects inequality. Gabaix, Lasry, Lions and Moll (2016), Jones and Kim (2018), and Aghion, Akcigit, Bergeaud, Blundell and Hemous (2019) argue that entrepreneurship and innovation affect income inequality. Acemoglu and Restrepo (2022) highlight the importance of automation technologies. Kumhof, Rancière and Winant (2015) investigate through which channels inequality leads to financial crises.

Building on the insight that richer households finance the borrowing of poorer households (Mian, Straub and Sufi, 2020), they argue high debt levels reduce aggregate demand, as borrowers must cut their spending to repay high-income savers with a lower propensity to consume. Auclert and Rognlie (2017, 2020) develop a theoretical model in which households' marginal propensity to consume declines in income. In quantitative experiments they show how rising inequality depresses aggregate demand and output in the short and long run. Beyond calibrating our model to cross-sectional estimates, an important difference in our setting is that inequality affects the economy through changes in firms' financing conditions, as households adjust the allocation of their savings.

Third, by linking rising inequality to the decline in job creation along the intensive and extensive margin, we speak to literature on declining dynamism and the rising footprint of large firms. Decker, Haltiwanger, Jarmin and Miranda (2014, 2016) document that the US economy has become less dynamic, in large part due to declining firm entry and exit. At the same time, the employment share of large firms has increased substantially over the last decades (Dorn, Katz, Patterson and Van Reenen, 2017; Autor, Dorn, Katz, Patterson and Van Reenen, 2020). The literature has provided a number of explanations for these trends, including demographics (Karahan, Pugsley and Şahin, 2022), adjustment frictions (Decker, Haltiwanger, Jarmin and Miranda, 2020), import competition (Pugsley and Sahin, 2019), and technological change (Autor, Dorn, Katz, Patterson and Van Reenen, 2020). Our findings suggest rising top income shares as another driver.

On the methodological side, to the best of our knowledge we develop the first macroeconomic model with an interaction between households' portfolio choices and employment decisions of firms with heterogeneous funding sources. For example, in Den Haan, Rendahl and Riegler (2017), households' portfolio choice between a liquid and a productive asset connects precautionary savings behavior with employment in a sector of identical firms. On the other hand, existing papers in which firms differ in their funding sources usually do not incorporate household portfolio decisions, see e.g. Zetlin-Jones and Shourideh (2017) and Crouzet (2018). As in Peter (2021), our model incorporates the possibility that private firms become public firms, a decision margin that is often left unmodeled in the firm dynamics literature.

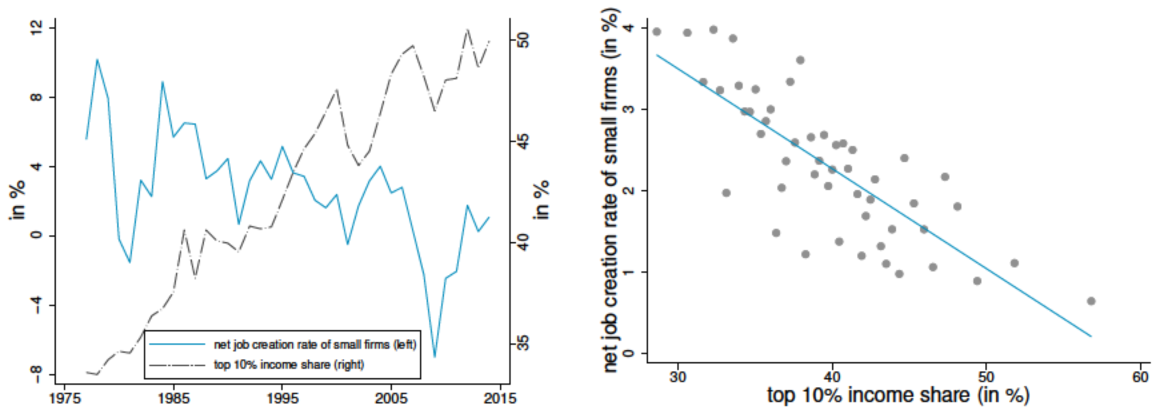
2 Motivating evidence and hypothesis

Figure 1, panel (a) shows two salient trends in the US economy: since the 1970s, the top 10% income share (black dashed line, right axis) has steadily increased. Meanwhile, net job creation at small firms (blue solid line, left axis) is in secular decline.

Panel (b), discussed in more detail below, shows a similar negative relationship between the top 10% income share and the net job creation rate of small firms when we look at individual state-year pairs. In fact, every single US state has seen an increase in its top 10% income share and a decline in the net job creation rate at small firms between 1975 and today.

Figure 1: **Top incomes and job creation**

(a) Over time (b) Across states



Note: Panel (a) shows the evolution of the top 10% income share over time (black dashed line, left axis) and the evolution of the net job creation rate of small firms with 1-499 employees (blue solid line, right axis) over time. Both series are averaged across states. Panel (b) provides a binned scatter plot with linear fit of the net job creation rate of small firms on the vertical axis and the top 10% income share on the horizontal axis across state-year cells in the sample. Source: Frank (2009) and BDS.

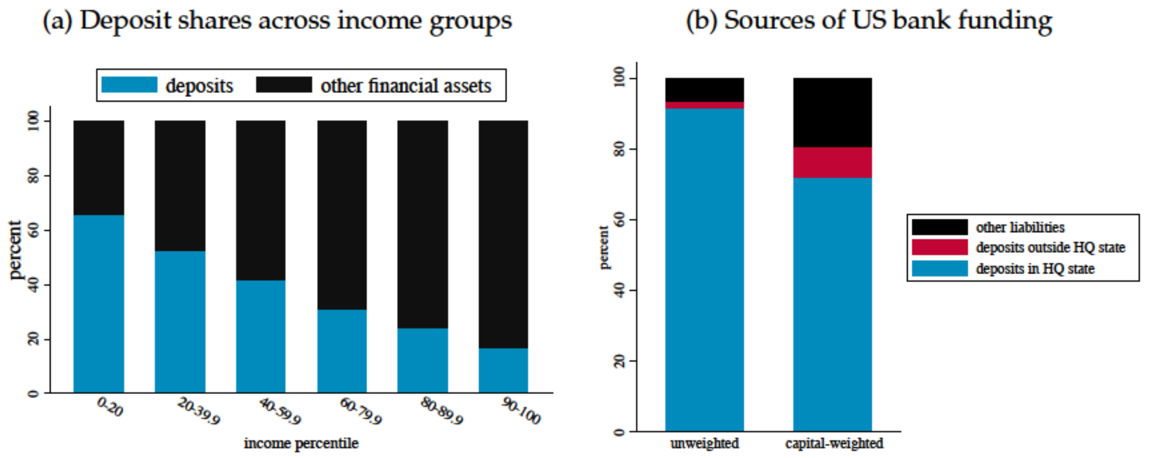
In this section, we argue that both developments are closely linked. To do so, we first present facts on the relation between household income and savings in different financial assets. Second, we examine the relevance of deposits for bank funding, and review the literature on the importance of bank lending for firms. Based on these motivating facts, we then develop our main hypothesis.

Household income and asset allocation. We examine the allocation of financial asset across the US household income distribution with data from the Survey of Consumer Finances (SCF) of the Federal Reserve.[4] Figure 2, panel (a) reveals that the share of financial assets held as deposits declines in household income (see also Wachter and Yogo (2010); Guiso and Sodini (2013)). Deposits represent around two-thirds of financial wealth for the bottom 20% of the income distribution, but less than one-fifth for the top 10%. Instead, the share of stocks, bonds, and other financial

[4]We combine the survey waves from 1992 to 2007, and compute the deposit share as the ratio of deposits to total financial wealth. We exclude non-financial assets. The SCF defines financial wealth as 'liquid assets, certificates of deposit, directly held pooled investment funds, stocks, bonds, quasi-liquid assets, savings bonds, whole life insurance, other managed assets, and other financial assets'. Non-financial wealth includes 'all vehicles, value of primary residence, value of other residential real estate, net equity in nonresidential real estate, value of business interests, and other financial assets'. The Online Appendix provides summary statistics.

assets increase with household income (see also Melcangi and Sterk (2020)).[5] These patterns suggest that the distribution of income across households matters for the allocation of household savings between bank deposits on the one hand and direct investments such as stocks and bonds on the other hand.

Figure 2: **Household asset allocation and bank funding sources**



Note: Panel (a) presents the allocation of households' financial wealth in deposits (defined as the sum of checking accounts, savings accounts, call accounts and certificates of deposit) and other financial assets (life insurance, savings bonds, money market (MM) deposits, money market mutual funds (MMMF) pooled investment funds, stocks, bonds, and other financial assets) by income group. Panel (b) provides a breakdown of banks' total liabilities into deposits held in branches located in the banks' headquarters state, deposits held in branches outside the banks' headquarters state, and liabilities other than deposits. Numbers reflect unweighted and capital-weighted averages across all banks and years in the sample. Sources: SCF and FDIC

While panel (a) presents relative *shares* of deposits, we show in the Online Appendix that the *level* of deposit holdings and income exhibit a log-linear relationship. This pattern reflects that high-income individuals have more resources to save, and is consistent with the economic mechanism we study throughout the paper.[6]

Deposits, lending, and bank dependence. The US banking system is, to this day, not fully deregulated. States use a variety of policy tools to protect local banks from outside competition (Rice and Strahan, 2010; Kroszner and Strahan, 2014), which explains why banks' headquarters state still plays an outsized role in their ability to raise deposits and engage in small business lending, as discussed in what follows.[7]

The Federal Deposit Insurance Corporation (FDIC) provides information on the sources of funding of all US banks. Figure 2, panel (b) shows that deposits account for 93% of total liabilities for the average bank between 1993 and 2015. On aggregate, deposits represent around 75% of total bank liabilities. Deposits' role as the major

[5]The SCF also accounts for assets in retirement accounts, for example stock ownership through a 401(k) account. The SCF does not account for future claims on social security benefits in households' financial assets, but it does include current social security payments in the calculation of income.

[6]The Online Appendix also provides a finer breakdown of asset classes and shows that the deposit share also declines in income within the top 10%. Furthermore, we verify that the negative relationship between income and the deposit shares is not explained by a large set of household controls, such as age, education level, occupation, or gender.

[7]See the Online Appendix, Section A.1, for more details on US banking deregulation.

source of cheap and stable funding in the US banking system suggests that households' willingness to save in deposits has an impact on banks' overall liabilities and ability to serve firms' loan demand.

The same panel reveals that the average bank raises around 98% of its total deposits in its headquarters state. Weighted by total bank capital, the respective number is 89%. The strong reliance on local deposits is also reflected in the fact that only 2% of banks hold more than 10% of their deposits in branches outside their headquarters state.[8] We exploit the regional dimension of bank funding in our identification strategy, following the idea that the *local* supply of deposits by households affects banks' funding conditions. In particular, as more money flows to top earners, who have a preference for holding high-return assets, banks need to offer higher deposit rates to raise funding to satisfy a given loan demand.

Banks' access to deposits as a cheap and stable source of funding affects their ability to extend credit (Ivashina and Scharfstein, 2010; Gilje, Loutskina and Strahan, 2016; Drechsler, Savov and Schnabl, 2017). The importance of deposits arises from their unique stability and dependability (Hanson, Shleifer, Stein and Vishny, 2015) and the fact that banks cannot replace them with other source of funding without incurring costs (Stein, 1998). Hence, an increase in deposit rates implies an increase in banks' overall funding costs, which – as banks need to maintain their profitability – translates into a higher cost of credit for firms, reducing loan demand (McLeay, Radia and Thomas, 2014; Jakab and Kumhof, 2015).[9]

The literature also highlights the importance of banks in screening and monitoring borrowers, which is especially relevant for firms that are informationally opaque (Gertler and Gilchrist, 1994; Liberti and Petersen, 2019). Consequently, a large literature shows that smaller firms, which are more difficult to screen and monitor, depend relatively more on bank lending (Petersen and Rajan, 1994), and that their investment and employment are more sensitive to changes in credit supply (Becker and Ivashina, 2014; Chodorow-Reich, 2014).[10] Likewise, banks play an outsized role

[8]See also Figure OA8 and Section A.1 in the Online Appendix. Even for the top-4 banks (JP Morgan, Citi, Wells Fargo, and Bank of America), the share of deposits raised in branches outside their headquarters state averages just 30%. Kundu, Park and Vats (2023) further show that for both small and large banks, at least 30% of deposits for a given bank are concentrated in a single county.

[9]By providing loans banks create new ledger-entry deposits on their balance sheet (Jakab and Kumhof, 2015). Their business model requires receiving higher interest on the loans than the interest paid on deposits (or other liabilities). McLeay, Radia and Thomas (2014) provide a detailed explanation of this process, emphasizing that banks need to "attract or retain additional liabilities to accompany their new loans". Considerations about profitability and liquidity risk thus create a positive relation between deposits rates and loan rates.

[10]Coleman and Carsky (1999) show that 92% of firms in the 1993 National Survey of Small Business Finances use banks to obtain credit. A frequent finding is that smaller banks have a comparative advantage in collecting local soft information and lend more to smaller firms (Berger, Klapper and Udell, 2001; Berger and Black, 2011).

in financing new firms (Robb and Robinson, 2014; Kerr and Nanda, 2015), suggesting that the availability of bank credit also affects firm entry.[11]

Main hypothesis. Motivated by these stylized facts, we propose a novel channel that links household savings behavior to firm financing and job creation: as the income share of top earners rises, a relatively larger amount of total financial assets is held in the form of stocks and bonds. Through this non-homotheticity in households' portfolio allocation, funding costs subsequently decline for firms that make greater use of equity and bond financing, which are generally large firms. Meanwhile, households' desire to save in deposits declines, increasing the cost of funds for banks as they must raise deposit rates to keep lending to firms. This argument holds even if lower-income households have lower overall savings rates than higher-income households.[12] Higher deposit rates lead to a relative increase in loan rates. Since banks have a comparative advantage in screening and monitoring, this increases the cost of financing for bank-dependent firms, which are predominately small firms and entrants. In turn, they create relatively fewer jobs.

3 Data and empirical strategy

This section first describes the data and main variables. It then explains our empirical strategy and the construction of the instrumental variable.

3.1 Data

Job creation. Data from the Business Dynamics Statistics (BDS), provided by the US Census Bureau, contain detailed yearly information on job creation at the state–firm size level for firms in 12 distinct size categories. The BDS provide a similar breakdown at the state–2-digit NAICS industry–firm size level. We define our baseline measure of *small firm* as firms with 1-499 employees, as is standard in the literature. Our main outcome variable is the net job creation rate (net JCR), defined as job creation rate minus job destruction rate (JDR). The net JCR hence captures overall job creation through entry, exit, and continuing establishment. An important advantage

[11] The Appendix shows that banks originate most of their small business loans in their home state.

[12] What is ultimately relevant in our hypothesis is how the *level* of deposit savings changes, relative to the *level* of other households savings, in response to changes in income inequality. If the level of funding available to bank-dependent firms increases relative to the amount of funding available to other firms, job creation at bank-dependent firms increases *relatively* more than at other firms. Our motivating evidence about *shares* of different savings types is directly connected to how the levels of different forms of savings respond to changes in income inequality. Online Appendix Section A.2 provides an additional discussion of our theoretical mechanism that formalizes the connection between shares and levels.

of the net JCR is that it can be decomposed into an extensive (entry and exit) and intensive (continuing establishments) margin.[13]

Top income shares. Frank (2009) provides annual data on income inequality and the share of income that accrues to the top 10% and top 1% across 48 states from 1917 to 2015. Income shares are derived from pretax adjusted gross income data reported in the Statistics of Income published by the Internal Revenue Service (IRS).[14] Income data include wages and salaries, capital income (dividends, interest, rents, and royalties), and entrepreneurial income. These data provide the most comprehensive state-level information on income shares for a longer time period.

Other state-level information. We obtain information on employment by 4-digit NAICS industry in each state from the County Business Patterns (Eckert, Fort, Schott and Yang, 2020). We also collect yearly state-level information on the total population, the share of the black population, the share of the population of age 60 and above (all provided in the Census Bureau's Population Estimates), the log difference in income per capita (Bureau of Economic Analysis), the Gini index (Frank, 2009), and the unemployment rate (Bureau of Labor Statistics' Local Area Unemployment Statistics). Finally, we collect state-level data on the number of venture capital deals from PWC's Money Tree Explorer; as well as on expenditures on education as a share of state-level GDP from the Census Bureau.

Bank dependence. We compute each industry's bank dependence (BD) from the 2007 Survey of Business Owners (SBO). The survey contains firms' sources of business start-up and expansion capital, as well as two-digit NAICS industry codes. Among firms with fewer than 100 employees that were founded before 1990, for each industry we compute the fraction of firms that report using bank loans to start or expand their business (Doerr, 2021). In the average industry one-third of firms obtain bank credit, with a standard deviation of 10%.[15] We split industries into high and low bank dependence along the median.

[13]The job creation (destruction) rate is the 'count of all jobs created (destructed) within the cell over the last 12 months' in year t, divided by 'the average of employment for times t and $t-1$'. We decompose the net job creation rate as follows: $net\ JCR = JCR - JDR = JCR\ births + JCR\ continuers - (JDR\ deaths + JDR\ continuers) = (JCR\ births - JDR\ deaths) + (JCR\ continuers - JDR\ continuers) = net\ JCR\ extensive + net\ JCR\ intensive$.

[14]Auten and Splinter (2023) show that while US *pre-tax* income inequality has risen in the last decades, *post-tax* inequality has increased less than previously shown by other authors. Our mechanism operates through changes in top income shares before taxation, as pre-tax income can be invested through e.g. 401(k) accounts. If high-income households' pre-tax earnings increase relative to low income-households, this results in relatively fewer deposits and relatively more purchases of other assets such as stocks, e.g. through the growth of pre-tax retirement accounts.

[15]Industries with the highest values of bank dependence are manufacturing (31–33), wholesale trade (42), transportation and warehousing (48–49) and management of companies and enterprises (55). Those with the lowest are finance and insurance (52), educational services (61), and arts, entertainment, and recreation (71).

Bank-level data. Our bank-level data are from the US Call Reports provided by the Federal Reserve Bank of Chicago, collapsed to the bank-year level (Drechsler, Savov and Schnabl, 2017). We obtain consistent data from 1985 to 2015 that contain information on the income statements and balance sheets of all commercial banks in the US. For each bank, we use the headquarters location to assign the respective evolution of state-level top incomes. We collect information on total deposits, deposit rates (defined as deposit expenses over total deposits), total assets, the share of non-interest income, return on assets, and leverage (defined as total assets over equity). We further collect data on total C&I lending, as well as interest income on C&I loans over total C&I loans, both of which are available only for a subset of banks.

Summary statistics. Our final panel has 16,435 state–firm size–year observations for 47 states from 1981 to 2015. Once we break down the data by industry, the panel expands to up to 192,968 state–firm size–industry–year observations. The sample for the bank-level regressions contains a total of 18,092 unique banks. The Online Appendix provides summary statistics (see Table OA5).

3.2 Empirical strategy

This section analyzes how rising top incomes affect job creation of bank-dependent firms relative to firms with access to other sources of financing. Motivated by a large literature on the importance of bank lending for small firms, our baseline analysis investigates the effect of top incomes on job creation of small relative to large firms.

Figure 1, panel (b) previews our main finding. It presents a binned scatter plot of the net job creation rate of small firms on the vertical axis against the top 10% income share on the horizontal axis at the state-year level. The blue line denotes the linear fit. The strong negative relationship suggests that a one standard deviation higher top 10% income share (5.4 p.p.) is associated with a 0.7 p.p. lower net job creation rate of small firms (equal to 0.22 standard deviations).

3.2.1 State-level empirical specification

We estimate the following regression:

$$\begin{aligned} net\ jcr_{s,f,t} = {} & \beta_1\ top\ 10\%\ income\ share_{s,t-1} + \beta_2\ small\ firm_f \\ & + \beta_3\ top\ 10\%\ income\ share \times small\ firm_{s,f,t-1} \\ & + controls_{s,t-1} + \theta_{s,f} + \tau_{s,t} + \epsilon_{s,f,t}. \end{aligned} \tag{1}$$

The dependent variable *net jcr* measures the net job creation rate by firms in size category f that are located in state s in year t. In some specifications, we decompose the net job creation rate into an extensive (entry and exit) and intensive margin. The *top* 10% *income share*$_{s,t-1}$ is the share of income that accrues to the top 10% in state s, lagged by one period. The dummy *small firm* takes on a value of one for firms with 1–499 employees, and zero for firms with 500 or more employees. We include the following set of lagged state-level controls: average income per capita growth, log population, the unemployment rate, the share of population age of age 60 and above, and the share of the black population. Standard errors are clustered at the state level to account for serial correlation among observations in the same state.

Our coefficient of interest is β_3, which measures the effect of top income shares on job creation of small relative to large firms. Our hypothesis implies $\beta_3 < 0$, as bank-dependent firms (i.e. small firms) should see a tightening in funding conditions as top income shares rise. The regressions include state or state-firm size fixed effects ($\theta_{s,f}$), which gives equation (1) an interpretation in terms of changes: a given increase in the state-level share of income that accrues to the top 10% decreases the net job creation of small firms, relative to large firms by β_3. By controlling for growth in *average* incomes, coefficient β_3 reflects the effect of a change in state-level top income shares on net job creation, holding average state-level income growth constant.

Identification and instrumental variable. The relationship between top income shares and job creation could be driven by reverse causality or omitted variable bias. Reverse causality could arise, for example, if shocks to large firms increase their job creation, and larger firms pay higher wages than small firms. Such shocks would lead to a relative decline in small firm job creation while raising income inequality through higher wages at large firms. Omitted variable bias could arise if unobservable state-level factors are simultaneously correlated with top income shares and job creation.[16]

To address these endogeneity issues and assess the causal effect of rising top income shares on job creation, we include granular time-varying fixed effects and develop an instrumental variable for the top income share.

Equation (1) includes state*time fixed effects ($\tau_{s,t}$). These fixed effects control for observable and unobservable time-varying characteristics at the state level that could affect job creation, for example technological change or globalization – two common explanations behind growing inequality (Cowell and Van Kerm, 2015). Any unobservable factor that could simultaneously drive job creation and top income shares hence needs to affect firms of different sizes within the same state. Moreover, in regressions at the state-industry level, we include time-varying fixed effects at the

[16] Another source of bias could arise if larger companies hold the extra financing they receive from high-income households primarily in the form of bank deposits. However, Darmouni and Mota (2024) show that large corporations put a significant share of their savings into marketable securities, rather than cash or bank deposits. They also show that even those corporate savings that are accounted for by 'cash and cash equivalents' are typically allocated to financial instruments such as money market fund shares or commercial paper instead of bank deposits.

state*industry level to account for trends at the state-industry level common to all firms. Any unobservable shock correlated with top income shares would then need to differently affect job creation of small and large firms e.g. only within the retail trade sector in California.

Our instrument (henceforth 'pre-determined share IV') uses each state's top 10% income share in 1970, ten years prior to our sample period, interacted with the national evolution in the top 10% income share. Specifically, we compute the 'leave-one-out' national trend by excluding each respective state from the nationwide evolution to adjust the pre-determined income share in that state: $top\ \widehat{10\%\ share}_{s,t} = top\ 10\%\ share_{s,1970} \times \frac{1}{S}\sum_{j\neq s}^{S} top\ 10\%\ share_{j,t}$. We then use the predicted top income shares as an instrument for the actual shares between the 1980 and 2015 in each state in equation (1). The IV has a highly significant positive relationship with the actual state-level top 10% (1%) income share.

The instrument has several desirable properties. First, top income shares remained flat between 1970 and 1980 (Figure OA1, panel b). Initial income shares are hence unlikely to be determined by trends that were already in operation before the 1970s and that could also have affected employment and wages at small and large firms. Moreover, the instrument's construction requires any such (unobservable) trend in a given state to exhibit a similar break around 1980 in all *other* states. Second, it excludes a mechanical relationship between large firms' job creation and income inequality. Such a relationship would arise if *i*) states with initially more large firms also had higher income inequality in 1970 because of large firms' wage premium, and *ii*) the initial footprint of large firms was positively correlated with an increase in the employment share of large firms going forward. We find no such systematic correlations (see Figure OA2 and Figure OA3).

We report several tests in the Online Appendix to support the validity of our instrument in Table OA4. There, we show the strong positive correlation between the IV and top income shares. We also estimate regressions at the state–sector level and exclude industries that account for a particularly large share of employment in a state, addressing the concern that an unobservable shock has a direct effect on employment in these industries and thereby affects top income shares. Further, we include state*sector*year fixed effects to absorb any common trends that affect firms within an industry in each state. These include industry concentration, import competition, or technological change. Finally, we exclude firms with 10,000 or more or 5,000 or more employees from the analysis, as these 'mega firms' experienced a substantial increase in employment and earnings. Our results remain robust.

In the Online Appendix we also construct a second instrument, which follows a shift-share research design. It is based on the insight that income inequality is driven by a small subset of industries (Haltiwanger, Hyatt and Spletzer, 2024). The instrument combines the beginning-of-sample employment shares of those industries that explain most of the overall increase in US income inequality with heterogeneity in the nation-wide employment trends for these industries over time.[17]

3.2.2 Bank-level empirical specification

Our hypothesis asserts that an increase in top income shares has a negative effect on households' desire to save in bank deposits. Banks hence need to increase deposit rates to continue to attract funds and meet their loan demand. However, an increase in banks' cost of funds increases the cost of credit for firms (McLeay, Radia and Thomas, 2014). An increase in the top income share in a state should thus have a positive effect on deposit rates and a negative effect on the amount of bank deposits, relative to states with less of an increase in the top income share. To provide direct evidence for these effects, we estimate the following bank-level regression:

$$\begin{aligned} y_{b,t} &= \delta \; top \; 10\% \; income \; share_{s,t-1} \\ &\quad + controls_{b,t-1} + controls_{s,t-1} + \theta_b + \tau_t + \epsilon_{b,t}. \end{aligned} \tag{2}$$

The dependent variable $y_{b,t}$ is either the deposit rate or the log amount of total deposits of bank b headquartered in state s in year t. The share of income that accrues to the top 10% is measured at the bank headquarters state s and instrumented with our pre-determined share IV. We include the same state-level controls as above, as well as the bank-level log of total assets, the share of non-interest income, return on assets, deposits over liability, and the leverage ratio, all lagged by one period. To reflect the skewed distribution in bank size, we weight regressions by total assets.

Each regression includes bank (θ_b) and year (τ_t) fixed effects that control for time-invariant bank characteristics and aggregate trends. Standard errors are clustered at the headquarters state level. The inclusion of bank fixed effects implies an interpretation in changes. If, for example, rising top incomes increase deposit rates, we expect $\delta > 0$. An important assumption underlying equation (2) is that banks raise a significant share of their deposits in their headquarters state. Figure 2, panel (b), shows that this is the case. The Online Appendix further shows that, while this ratio declines in bank size and over time, even in 2015 the vast majority of banks raise the lion's share of their deposits in their headquarters state. Even the four largest US banks raise over 70% of their deposits in their headquarters state. However, to

[17] This IV has two limitations. First, the analysis in Haltiwanger, Hyatt and Spletzer (2024) on LEHD data is from 1990 onward. We hence cannot construct the IV for our full sample period without making the assumptions that the same 30 industries drive inequality before 1990. Second, unlike the IV based on pre-determined shares, it does not allow us to construct separate instruments for the top 10% and top 1% income share.

the extent that banks raise deposits outside their headquarters state, this leads to an attenuation bias and the coefficient δ would reflect a lower bound of the true estimate.

4 Results of the empirical analysis

Table 1 shows evidence consistent with our main hypothesis that rising top income shares reduce job creation of bank-dependent firms. It reports 2SLS results for equation (1).[18] Column (1) employs state and year fixed effects, as well as state-level controls. Rising top income shares are associated with lower net job creation rates on average ($\beta_1 < 0$), and small firms have higher average net job creation rates ($\beta_2 > 0$). Importantly, higher top income shares significantly reduce net job creation rates of small firms, relative to larger firms ($\beta_3 < 0$), in line with our hypothesis.

Table 1: **Rising top incomes and job creation**

VARIABLES	(1) net JCR	(2) net JCR	(3) extensive net JCR	(4) intensive net JCR	(5) net JCR	(6) low BD net JCR	(7) high BD net JCR
top 10% income share	-0.017						
	(0.129)						
small firm (1-499)	0.056***						
	(0.009)						
top 10% × small firm (1-499)	-0.124***	-0.161***	-0.027**	-0.133***		-0.255***	-0.348***
	(0.021)	(0.022)	(0.011)	(0.016)		(0.034)	(0.033)
top 10% × firms with 1-9 emp					-0.315***		
					(0.037)		
top 10% × firms with 10-99 emp					-0.098***		
					(0.023)		
top 10% × firms with 100-499 emp					-0.049***		
					(0.017)		
Observations	16,435	16,435	16,435	16,435	16,435	60,372	63,823
Controls	✓	-	-	-	-	-	-
State FE	✓	-	-	-	-	-	-
Year FE	✓	-	-	-	-	-	-
State*Size FE	-	✓	✓	✓	✓	✓	✓
State*Year FE	-	✓	✓	✓	✓	-	-
State*Industry*Year FE	-	-	-	-	-	✓	✓
F-stat	95.43	300.8	300.8	300.8	128.4	282.1	275.9

Note: This table reports results from regression (1) at the state-firm size-year level in columns (1)–(5) and at the state-industry-firm size-year level in columns (6)–(7). The dependent variable is the net job creation rate. Columns (3) and (4) use the net job creation rate along the extensive and intensive margin as dependent variables. The variable *top 10% income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the IV based on predetermined income shares. The variable *small firm* is a dummy with a value of one for the group of firms with 1 to 499 employees; In column (5), small firms are separated into firms with 1 to 9, 10 to 99, and 100 to 499 employees. *Low/high BD* refers to industries with low/high dependence on bank lending. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1. F-stat refers to the first-stage F-statistic.

[18] We provide results from OLS regressions in the Online Appendix. See Table OA11. Coefficients from OLS regressions are similar in terms of sign and significance to those obtained in IV regressions, but OLS estimates are about a quarter smaller in magnitude. This could reflect measurement error in the top income share.

Column (2) uses state–firm size and time-varying fixed effects at the state level. The former account for time-invariant factors that affect firm size groups in a given state, and the latter for unobservable time-varying state-level characteristics that could affect net job creation. The coefficients on *small firm* and *top* 10% *income share* are absorbed by the fixed effects. The coefficient on the interaction term between the top 10% income share and the small firm dummy remains highly significant and increases in magnitude relative to column (1).

To put our estimates into perspective, the US-wide increase in the income share of the top 10% from 1980 to 2015 was around 16 p.p. Hence, relative net job creation of small firms would have been 1.9–2.6 p.p. higher today had top incomes remained at their 1980 levels. Relative to the average job creation of small firms during the 1980s, which equaled 3.3%, the effect is economically large.

4.1 Intensive vs. extensive margin

Decker, Haltiwanger, Jarmin and Miranda (2014) and Sterk, Sedlacek and Pugsley (2021) highlight the important role of firm entry and exit for aggregate dynamism and productivity growth. Columns (3) and (4) split the overall net job creation rate by small firms into job creation along the extensive (job creation and destruction through entry and exit) and the intensive margin (job creation and destruction by continuing firms).

Rising top income shares lead to significantly lower net job creation rates along both margins. In terms of magnitude, the effect on the extensive margin (coefficient estimate of -0.027) is around one-fifth as large as on the intensive margin (-0.133). In other words, out of the overall decline in small firms' net job creation rate due to an increase in the top 10% income share, around 20% stem from a reduction of net job creation along the entry-exit margin. The fact that the extensive margin effect is weaker may be because more income in the hands of high income individuals could also positively affect new business creation through a separate net worth channel (Hurst and Lusardi, 2004; Cagetti and De Nardi, 2006).

While new businesses have an outsized influence on job creation and growth, the rate of business startups has declined in recent decades (Decker, Haltiwanger, Jarmin and Miranda, 2016). To investigate the effects of rising inequality on firm entry, we focus on gross job creation of entrants (rather net job creation through entry and exit) in the Online Appendix (see Table OA8). We first show that a rise in the top income share has a significant negative effect of on the gross job creation rate of small firms. The inequality-induced decline in job creation of entrants accounts for almost 50% of this overall effect. Consistent with this finding, a higher top 10% income share also leads to a relative decline in the number of young firms.

The average gross job creation rate at small firms during the 1980s equaled about 19%. Our estimates suggests that, had top incomes remained at their 1980 levels, relative gross job creation of small firms would have been about 33% higher, out of which almost half (or 16%) are due to depressed entry. Taking into account entry and exit, small firms' net job creation rate along the extensive margin averaged 1.6% during the 1980s. The 0.43 p.p. decline induced by the 16 p.p. increase in the top 10% between 1980 and 2015 hence reflects a 27% drop in the net job creation rate through lower entry and exit.

4.2 Further evidence on the mechanism

Banks have a comparative advantage in screening and monitoring opaque firms (see the discussion in Section 2). Small firms are informationally more opaque, so they depend more on banks as a source of credit than larger firms. The relative effect of a given increase in top income shares on job creation should therefore decline in firm size. Column (5) in Table 1 supports this argument by separating the small firm dummy into finer categories: while a 10 p.p. increase in the top 10% income share reduces the net job creation rate by 3.2 p.p. for very small firms with 1-9 employees, net job creation declines by 0.98 p.p. and 0.49 p.p. for small (10-99 employees) and medium (100-499 employees) firms, relative to firms with 500 or more employees.

Next we exploit variation in the importance of banks across industries. If small firms in an industry depend more on bank funding, a relative increase in the cost of credit should hurt firms in this industry by more than those in other industries. We estimate regressions analogous to (1), but at the state-industry-firm size-year level. Specifically, we estimate regressions separately for industries in the bottom (low BD) and top (high BD) tercile of bank dependence. Columns (6)–(7) show that the negative effect of rising top income shares on job creation of small relative to large firms is significantly larger in bank-dependent industries. A 10 p.p. increase in top 10% income shares leads to a relative decline in job creation among small firms of 2.6 p.p. in low bank-dependence industries in column (6). The corresponding number is 3.5 p.p. in high bank-dependent industries in column (7). As we show in the Online Appendix, rising top income shares have a relatively stronger effect on job creation both along the intensive and extensive margin in bank-dependent industries.

Taken together, Table 1 provides evidence consistent with our proposed mechanism. A rise in top income shares reduces job creation of smaller firms, both along the extensive and intensive margin. It does so especially among the smallest firms, as well as those that operate in bank-dependent industries.

4.3 Top incomes and bank deposits

Our hypotheses suggest that as income inequality increases, households will save less in deposits. In response, banks need to offer higher deposit rates to attract a given amount of deposits. Table 2, columns (1)–(2) use the deposit rate as dependent variable and show that the price of deposits increases significantly as top income shares rise. In column (1), a 10 p.p. increase in the predicted top income share increases the deposit rate by 1.06 p.p. (28% of the mean) for the average bank, relative to banks in states with no change in the top income share. As discussed in Section 2, a given increase in the top 10% income share should affect banks' ability to raise deposits by relatively less than a similar increase for the top 1%. The reason is that the latter hold an even lower share of their financial wealth as deposits (see panel (b) of Figure OA5 in the Online Appendix). To test this hypothesis, we estimate equation (2), but use the $top\ 1\%\ income\ share_{s,t-1}$ as independent variable. Column (2) shows that the coefficient increases in magnitude, consistent with the fact that the share of deposits out of financial assets declines in household income.[19]

Table 2: **Rising top incomes and bank deposits**

VARIABLES	(1) dep rate	(2) dep rate	(3) log(dep)	(4) log(dep)	(5) CI rate	(6) log(CI)
top 10% income share	10.606***		-2.328***		46.619**	-2.405***
	(2.580)		(0.576)		(19.373)	(0.657)
top 1% income share		11.768***		-4.928***		
		(4.306)		(1.134)		
Observations	242,651	242,651	242,651	242,651	112,393	112,393
Bank FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
F stat	117.1	89.52	117.1	89.52	77.45	77.45

Note: This table reports results from regression (2) at the bank-year level. The dependent variable is the deposit rate in columns (1)–(2) and the log amount of total bank deposits in columns (3)–(4). In columns (5)–(6), the dependent variable is the ratio of C&I interest income to total C&I lending and the log amount of total bank C&I lending. *top* 10/1% *income share* is the share of income that accrues to the top 10/1% in state *s*, lagged by one period. All regressions include state and bank controls and are weighted by total bank assets. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. F-stat refers to the first-stage F-statistic.

Columns (3) and (4) use the log of total deposits as dependent variable. Column (3) shows that a 10 p.p. increase in the instrumented top income share leads to a 23% decline in bank deposits for the average bank, relative to banks in states with no change in the top income share. The coefficient is significant at the 1% level. To put these results into perspective, the top 10% income share has increased by around 16

[19] We confirm in the Online Appendix that a similar increase in top 1% (rather than top 10%) income share also leads to an stronger negative effect on job creation of small firms.

p.p. between 1980 and 2015. Over the same period, aggregate deposits as a share of household non-financial assets have declined by around 50% (see Figure OA7 in the Online Appendix). Column (4) again shows that estimated coefficients are larger for the 1% income threshold.

The results in columns (1) to (4) suggest that a rise in top income shares leads to a relative increase in the *price* of deposits and a relative decline in their *quantity*. This pattern is consistent with a relative decline in the supply of local deposits by households as state-level top income shares rise. In response, banks need to raise deposit rates to attract funding and continue lending. These results also make clear that the partial effect of higher top income shares on deposit quantities can to some degree be counteracted by the equilibrium response of deposit rates. Our structural model will account for the general equilibrium changes in both the price and the quantity of deposits, as well as implications for bank lending.

Loan rates and lending. Finally, columns (5)–(6) of Table 2 show that higher top incomes also increase banks' interest income on C&I loans and decrease their C&I lending. Thus, as for deposits there is an increase in prices (loan rates) and a decrease in quantities as inequality rises. This pattern suggests that rising top incomes, through their effect on the cost of bank deposits, affect banks' credit supply to firms, thereby hurting bank-dependent businesses more than those that can access other forms of financing. While bank-level data on bank lending do not allow us to directly control for confounding factors, such as changes in loan demand, the observed pattern is in line with our mechanism.[20]

4.4 Alternative explanations and additional results

Alternative channels. We examine alternative explanations for the link between top income shares and job creation of firms of different sizes in the Online Appendix (see Table OA6). First, our results remain similar when we control for state-level house price growth or exclude states with a housing boom, suggesting that the relationship is not explained by a collateral channel (Chaney, Sraer and Thesmar, 2012; Adelino, Schoar and Severino, 2015). Second, venture capital is an important source of financing for startups and could possibly substitute for the decline in bank lending to firms (Kerr and Nanda, 2015). Our results are robust when we exclude states that account for the majority of venture capital funding or directly control for the amount of venture capital deals. Third, controlling for education spending does not affect

[20] The Online Appendix shows that the effects on deposits and loan amounts are significantly less pronounced among larger banks. Furthermore the effects of rising top incomes on net job creation are stronger in states where the median bank is smaller, and in states that have more banks per capita – reflecting that smaller banks are more likely to finance small firms (Berger, Miller, Petersen, Rajan and Stein, 2005).

our results, which ensures that our channel is distinct from Braggion, Dwarkasing and Ongena (2021). We also move to state-industry-firm size-year level regressions and control for time-varying confounding factors at the state-industry level through granular state*industry*year fixed effects. Our coefficient of interest remains near-identical in terms of sign, size and significance. In state-industry-firm size-year level regressions we also can exclude non-tradable industries (see Table OA7). Results remain similar, addressing the concern that high-income households demand more services (Boppart, 2014) that might be predominately provided by local, more bank-dependent smaller firms. In additional robustness tests we exclude the years of the Great Recession, years of economic downturns, and the post-crisis period.

Adding a second instrument. To add power to our instrumental variable estimation, we combine our instrument based on pre-determined shares with the Bartik instrument. Table OA12 in the Online Appendix presents the results from the IV regressions of job creation on the two instruments combined. As in Table 1, the coefficients on the interaction terms are always negative and significant, and similar in magnitude. The F-statistics for the two instruments combined is always above 100.

5 Macroeconomic model

This section develops a macroeconomic model that incorporates the link between income inequality, household portfolios, and job creation of firms with access to different sources of funding. We calibrate the model's parameters to match our empirical estimates. Section 6 presents quantitative model experiments.

5.1 Model setup

Time is denoted by $t = 1, 2, ...$ and continues indefinitely. The economy is populated by a continuum of infinitely-lived households and a continuum of firms that are either private or public. We use 'private' and 'public' as shorthand for bank-dependent, smaller firms and large firms with access to capital markets, analogous to our classification of firms in the empirical analysis. We denote variables and parameters pertaining to private firms with a tilde ("$\sim$"). The model also features a representative bank. We describe these agents in turn.

Households. There is a unit mass of households indexed by i, which differ in their idiosyncratic income risk $s_{i,t}$. Each household supplies labor to both private and public firms, taking respective wages $\widetilde{w}_t$ and w_t as given. Households decide how much to consume, how much to save, and how to allocate their savings between bank deposits $d_{i,t}$ or direct investments in public firms $k_{i,t}$. The returns on these two assets are $R_{d,t}$ and $R_{k,t}$. Deposits and investments differ in the services they provide. We assume that bank deposits give utility. This implies that $R_{d,t} < R_{k,t}$ in equilibrium. A household's within-period utility flow is

$$u(c_{i,t}, n_{i,t}, \widetilde{n}_{i,t}) + v(d_{i,t}) = \frac{\bar{u}(c_{i,t}, n_{i,t}, \widetilde{n}_{i,t})^{1-\sigma}}{1-\sigma} + \psi_d \frac{d_{i,t}^{1-\eta}}{1-\eta}, \tag{3}$$

where $c_{i,t}$ is consumption and $\widetilde{n}_{i,t}$ and $n_{i,t}$ are labor supplied to private and public firms. We assume $\eta > \sigma$, which generates non-homotheticity in preferences, making deposits a *necessity good*. This assumption allows us to generate in a tractable way the empirical fact that the share of deposits in savings decreases in income. De Nardi (2004) and Straub (2019) make a similar assumption to generate an increasing share of overall savings, by making wealth (bequests) a *luxury good*.[21] Our assumption stands in for unmodeled determinants of the deposit share along the income distribution. One example are liquidity services that benefit households at different income levels, e.g. because of health risk.[22] The Online Appendix provides evidence from the SCF that households' self-reported liquidity needs relative to income fall with income.

The household's objective is to maximize expected lifetime utility

$$\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left\{ u\left(c_{i,t}, n_{i,t}, \widetilde{n}_{i,t}\right) + v\left(d_{i,t}\right) \right\} \right], \tag{4}$$

subject to

$$c_{i,t} + d_{i,t+1} + k_{i,t+1} = s_{i,t}\left(w_t n_{i,t} + \widetilde{w}_t \widetilde{n}_{i,t}\right) + R_{k,t} k_{i,t} + R_{d,t} d_{i,t} + \Pi_{i,t} - T_{i,t}, \tag{5}$$

$$d_{i,t+1}, k_{i,t+1} \geq 0, \tag{6}$$

where $\Pi_{i,t}$ are profit rebates from firms and $T_{i,t}$ is a lump-sum transfer or tax. In our main quantitative experiment, we introduce changes in $\{T_{i,t}\}_i$ to generate a change in the top income share that matches its evolution since the early 1980s.

Firms. There is a continuum of firms, indexed by j. Firms consist of two types, private and public. The share of each type is endogenously determined. For a firm of either type, idiosyncratic productivity is denoted by $z_{j,t}$. As it is common in firm dynamics models (Hopenhayn, 1992), $z_{j,t}$ is independent across firms and follows a first-order Markov process. Its autocorrelation is ρ_z and its standard deviation is σ_z.

[21] In our model, while deposits shares fall in income, overall savings shares (the sum of capital and deposits relative to income) can rise in income, as in Straub (2019).

[22] Equity holdings are generally less liquid because in the US a large share are held through retirement accounts (Melcangi and Sterk, 2020). Private equity holdings, widespread among high income earners, are typically also less liquid than bank deposits. Another example of a structural factor could be differences in financial literacy or sophistication across the income distribution.

Each period, a mass $\widetilde{\mu}_e$ of private firms enter the market. In a given period, a private firm can either produce, transition to become a public firm, or exit the market. When producing, it produces consumption good $\widetilde{y}_{j,t}$ according to

$$\widetilde{y}_{j,t} = z_{j,t}\widetilde{n}_{j,t}^{\widetilde{\alpha}} - \widetilde{f}_{j,t},\ \widetilde{\alpha} < 1, \tag{7}$$

where $\widetilde{n}_j$ is firm j's employment. The fixed cost $\widetilde{f}_{j,t}$ is stochastic and independently and identically distributed uniformly over the interval $[0, \widetilde{f}_{max}]$. Decreasing returns ($\widetilde{\alpha} < 1$) pin down a firm's size (Lucas, 1978).

Private firms do not have access to public capital markets, but instead require bank loans. Specifically, they finance both their fixed cost and a share $\widetilde{\phi}$ of their wage bill before production using a bank loan at gross interest rate $R_{\ell,t}$. The value of an operating private firm with productivity level $z_{j,t}$ and fixed cost $\widetilde{f}_{j,t}$ is

$$\widetilde{V}(z_{j,t}, \widetilde{f}_{j,t}) = \max_{\widetilde{n}_{j,t}} z_{j,t}\widetilde{n}_{j,t}^{\alpha} - R_{\ell,t}\widetilde{f}_{j,t} - \{1 + \widetilde{\phi}(R_{\ell,t} - 1)\}\widetilde{w}_t\widetilde{n}_{j,t} + \beta_f \mathbb{E}_t\left[\widetilde{W}(z_{j,t+1})|z_{j,t}\right], \tag{8}$$

where β_f is the discount factor common to both firm types and $\widetilde{W}(z_{j,t+1}|z_{j,t})$ is the value of the private firm at the beginning of the period $t+1$. The optimal choice of employment is given by

$$\widetilde{n}^*(z_{j,t}) = \left[\frac{\widetilde{\alpha} z_{j,t}}{\{1 + (R_{\ell,t} - 1)\widetilde{\phi}\}\widetilde{w}_t}\right]^{\frac{1}{1-\widetilde{\alpha}}}. \tag{9}$$

If a private firm's value is less than zero, it is optimal to exit the market. Thus, for a given level of productivity, there is a cutoff fixed cost $\widetilde{f}^*(z_{j,t})$ above which a firm with productivity level $z_{j,t}$ exits. It is pinned down by

$$\widetilde{V}(z_{j,t}, \widetilde{f}^*(z_{j,t})) = 0. \tag{10}$$

A private firm can transition to become a public firm, which allows it to obtain an additional funding source by accessing capital markets (Peter, 2021). In our framework, this transition away from bank-dependence is an endogenous choice for private firms. At the beginning of period t, the cost of becoming a public firm $\widetilde{\kappa}_{j,t}$, independently and identically distributed uniformly over the interval $[0, \widetilde{\kappa}_{max}]$, is realized. Then, each private firm decides whether to become a public firm or not. If a firm chooses not to, then it operates as a private firm and the fixed cost of production is realized. If a firm decides to pay the cost $\widetilde{\kappa}_{j,t}$, it becomes a public firm and produces as a public firm in the same period. The transition decision is based on whether the value of becoming public exceeds that of remaining private, resulting in a cutoff cost $\widetilde{\kappa}^*(z_{j,t})$ pinned down by

$$V(z_{j,t}) - \widetilde{\kappa}^*(z_{j,t}) = \int_0^{\widetilde{f}^*(z_{j,t})} \widetilde{V}(z_{j,t}, x) d\Phi_{\widetilde{f}}(x), \tag{11}$$

where $V(z_{j,t})$ is the value of being a public firm, defined below. $\Phi_{\widetilde{f}}$ is the cumulative distribution function of fixed costs.

The value of a private firm at the beginning of the period can now be defined as

$$\widetilde{W}(z_{j,t}) = \widetilde{p}(z_{j,t})\{V(z_{j,t}) - \bar{\kappa}(z_{j,t})\} + \{1 - \widetilde{p}(z_{j,t})\} \int_0^{\widetilde{f}^*(z_{j,t})} \widetilde{V}(z_{j,t}, x) d\Phi_{\widetilde{f}}(x), \tag{12}$$

where $\widetilde{p}(z_{j,t}) = Prob(\widetilde{\kappa}_{j,t} \leq \widetilde{\kappa}^*(z_{j,t}))$ is the probability of becoming a public firm. $\bar{\kappa}(z_{j,t}) = \int_0^{\widetilde{\kappa}^*(z_j)} x d\Phi_{\widetilde{\kappa}}(x)$ is the expected cost incurred when optimally transitioning to become a public firm for firms with productivity level $z_{j,t}$, where $\Phi_{\widetilde{\kappa}}$ is the cumulative distribution function of $\widetilde{\kappa}_{j,t}$.

A private firm's optimal behavior is characterized by $\{\widetilde{n}^*(z_{j,t}), \widetilde{f}^*(z_{j,t}), \widetilde{\kappa}^*(z_{j,t})\}$. Using the optimality conditions it can be shown that, for a given wage, $\frac{\partial \widetilde{n}^*_{j,t}}{\partial R_{\ell,t}} < 0$, $\frac{\partial \widetilde{f}^*_{j,t}}{\partial R_{\ell,t}} < 0$, $\frac{\partial \widetilde{\kappa}^*_{j,t}}{\partial R_{\ell,t}} > 0$, $\frac{\partial^2 \widetilde{n}^*_{j,t}}{\partial R_{\ell,t}\, \partial \widetilde{\phi}} < 0$, $\frac{\partial^2 \widetilde{f}^*_{j,t}}{\partial R_{\ell,t}\, \partial \widetilde{\phi}} < 0$, and $\frac{\partial^2 \widetilde{\kappa}^*_{j,t}}{\partial R_{\ell,t}\, \partial \widetilde{\phi}} > 0$. These comparative statics reveal how the model captures the findings of our empirical analysis. In general equilibrium a higher top income share reduces aggregate deposit supply, pushing up the loan rate. In the private firms' problem, a higher loan rate suppresses employment demand of private firms due to the working capital constraint. It also makes it less attractive for firms to stay in the market and more attractive to become a public firm, as the value of being a private firm decreases when loan rates are higher. The strength of these intensive and extensive margin effects is driven by the degree of bank dependence of the private firm sector, which allows our calibration to match the empirical magnitude of the effect of higher top income shares on small firm employment through a suitable value of the working capital parameter $\widetilde{\phi}$.

We now turn to the description of public firms. They produce consumption good $Y_{j,t}$, using both capital $K_{j,t}$ and labor $N_{j,t}$, according to production function

$$Y_{j,t} = z_{j,t} K_{j,t}^{\theta} N_{j,t}^{\gamma - \theta}, \tag{13}$$

where $0 < \theta < 1$ is the share of capital, and $\theta < \gamma \leq 1$ governs the returns to scale in production. Note that public firms' productivity is governed by the same stochastic process as private firms'. The value of a public firm with productivity level $z_{j,t}$ is

$$V(z_{j,t}) = \max_{K_{j,t},N_{j,t}} z_{j,t} K_{j,t}^{\theta} N_{j,t}^{\gamma-\theta} - (R_{k,t} + \delta - 1) K_{j,t} - w_t N_{j,t} + \beta_f (1-\lambda) \mathbb{E}_t \left[V(z_{j,t+1}) | z_{j,t} \right], \tag{14}$$

where λ is the exogenous exit probability of public firms and δ is the depreciation rate. Profit maximization implies

$$R_{k,t} = \theta z_{j,t} \left(K_{j,t}\right)^{\theta-1} \left(N_{j,t}\right)^{\gamma-\theta} + 1 - \delta, \tag{15}$$

$$w_t = (\gamma - \theta) z_{j,t} \left(K_{j,t}\right)^{\theta} \left(N_{j,t}\right)^{\gamma-\theta-1}. \tag{16}$$

This firm's funding is 'public' in the sense that there are no agency conflicts or other frictions that prevent households from undertaking direct investments into the capital of this firm. In other words, public firms do not need bank funding.

Banking sector. A representative bank operates in a perfectly competitive environment. It offers deposits to households and grants loans to private firms. We assume that banking operations require a fixed cost Ξ. The bank pays gross interest rate $R_{d,t}$ on deposits and lends at gross rate $R_{\ell,t}$. Since there is no uncertainty associated with private firms, the bank does not face default risk. The bank's zero profit condition and the loan market clearing condition imply

$$R_{\ell,t} = R_{d,t} + \frac{\Xi}{D_{t+1}}, \tag{17}$$

where D_t is the total amount of deposits in the economy.

Since our model features rich heterogeneity on the household and firm side, we keep the bank's problem stylized for tractability. The main role of the banking sector is that in equilibrium it connects deposit supply and loan demand, and thereby the income distribution and job creation. Households' deposit supply is upward-sloping, as higher deposit rates make deposits more attractive. Importantly, banks need to offer a higher deposit rate to raise a given amount of deposits in a more unequal society. The reason is that deposits have a non-pecuniary benefit that is stronger for low-income households. Loan demand by private firms is downward-sloping, as higher loan rates make borrowing more costly.

These features imply that when a higher share of income accrues to the top earners, banks need to offer a higher deposit rate. As this higher deposit rate translates into a higher loan rate, banks move along the downward-sloping loan demand function, so that the equilibrium amount of lending falls. A higher loan rate suppresses private firms' ability to hire labor – their job creation declines. This interplay between households, firms and the banking system in the model generates the relationships that our empirical analysis uncovers in Tables 1 and 2.

Market clearing and model solution. The Online Appendix provides a definition of the stationary equilibrium and a detailed description of the algorithm. Although the model features both heterogeneous households and heterogeneous firms, it can be solved with a relatively straightforward algorithm. It is akin to solving an Aiyagari (1994) model, but with a nested loop structure in which quantities and prices in different markets are guessed. We iterate over these guesses until all markets clear.

5.2 Specification and calibration

Our strategy is to characterize a stationary equilibrium that captures the aggregate US economy in the early 1980s, i.e. the beginning of the sample period of our empirical analysis. In this equilibrium, we match household portfolio shares across the income distribution to the SCF, as well as features of the firm size distribution to the BDS. We then carry out a model experiment that increases the top income share in line with its actual evolution from 1980 to today. In this experiment, we directly match our estimated responses of the net job creation among firms of different sizes to changes in the top income share, both at the extensive and intensive margin.

Income risk and preferences. Heterogeneity across households comes from ex-ante and ex-post differences in idiosyncratic labor income risk $s_{i,t}$. There are permanent ex-ante differences between two types of households $\chi = L, H$, with mean s_χ and mass μ_χ. Type $\chi = L$ gets lower income draws in expectation than type $\chi = H$. The ex-post differences arise from the realized income draws, which are idiosyncratic also within the two type groups. This generates the idiosyncratic risk standard in incomplete markets models. Formally, household i of type χ faces the process $s_{i,\chi,t} = s_\chi \xi_{i,t}$ with $\log \xi_{i,t} = \rho \log \xi_{i,t-1} + \varepsilon_{i,t}, \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$, where ρ and σ_ϵ are the persistence and standard deviation, common across all households. $s_H \neq s_L$ allows for permanent income differences, and we calibrate these parameters to match the initial top 10% income share in US data. We specify $\bar{u}(c_i, n_i, \widetilde{n}_i, s_i) = c_i - \psi_n s_i \frac{n_i^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}} - \widetilde{\psi}_n s_i \frac{\widetilde{n}_i^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$. In our main experiment, both household types work at both firm types. In an additional model experiment, we assume that household type L works at private and type H at public firms.

Categorization of public and private firms. We calibrate the public and private firm sectors such that private firms represent companies with less than 500 employees. This definition is in line with the standard definition of "small and medium enterprises", see e.g. Caglio, Darst and Kalemli-Özcan (2022), and reflects our econometric choice of firm size as a proxy for bank-dependence.

Net job creation vs. employment. While our empirical analysis uses the net job creation rate (i.e. a growth rate), the model does not feature employment growth in the stationary equilibrium. We target the percentage point change in the net job creation rate in response to rising top income shares in our empirical estimates (Table 1) with the percentage change in employment. This assumption likely understates the effects of rising inequality on employment levels, because a change in the growth rate implies a similar level difference only as long as the change is temporary. If the change in the net job creation rate is persistent or permanent, then the resulting level change in employment would be larger and our channel would have a stronger effect on macroeconomic outcomes.[23]

Structural parameters. The model's frequency is annual. We first set a few standard parameters to external values common in the literature. We then internally calibrate the remaining parameters to target empirical moments related to households' income and portfolio shares, firms' employment shares, and our identified response of net job creation rates to changes in top income shares.

Panel (a) of Table 3 presents the externally calibrated parameters. We set the coefficient of relative risk aversion to 1.5 and the Frisch elasticity to 3. The persistence of the idiosyncratic income process is 0.92, implying a quarterly autocorrelation of 0.98. The standard deviation is set to 0.12, based on Storesletten, Telmer and Yaron (2004). The mass of each household type captures the size of the top 10% and bottom 90% income groups. The degree of decreasing returns to scale in private firms' production function $\widetilde{\alpha}$ is set to 0.99. We set $\lambda = 0.1$. The mass of entrants of private firms $\widetilde{\mu}_e$ is set to 0.1527 to normalize the mass of firms to 1 in the initial steady state.

Panel (b) presents the internally calibrated parameters. Total hours worked and initial wages are normalized to 1. We set the coefficients of labor disutility ψ_n and $\widetilde{\psi}_n$ such that the shares of public and private firm labor that households supply matches the corresponding employment shares in the BDS in 1981 (46.9% and 53.1%). ψ_d determines the desirability of deposits relative to capital, while η determines how rapidly marginal utility of deposits falls with income. We calibrate these parameters to match the deposit share of the middle quintile and the top 10% income in the SCF

[23]Suppose employment of small and large firms equals 1 each (in 1980 both make up roughly half of employment, so this normalization is applicable). Suppose their net job creation rates are 6% and 3%. Then the percent level difference in employment after one year is $\frac{1.06}{1.03} - 1 \approx 3\%$. Suppose now, because of higher top income shares, the small firm net job creation rate falls to 4%. The level difference is instead $\frac{1.04}{1.03} - 1 \approx 1\%$. That is, the fall of 2 p.p. in the rate is equal to a 2% relative level change. If the growth rate stays lower in subsequent years, the level difference grows, but we calibrate the model only to 2% level difference in this example, consistent with a one-off change.

in the early 1980s (0.45 and 0.22). β governs households' overall desire to save, and is calibrated to match the net return on public firms' capital to the historical average of US stock returns of around 8%. We set β_f to the same value. s_L is normalized to 1, while s_H is calibrated to ensure that the initial top 10% income share equals 34.5%, the starting point of our experiments. In line with the Frank (2009) data used in our empirical analysis, total income consists of labor income, asset income, and profits.

Table 3: **Model parameterization to target the US economy in the early 1980s**

Panel (a): externally calibrated parameters

Parameter and description		Value	Parameter and description		Value
σ	Relative risk aversion	1.50	μ_L	Mass of L type households	0.9
ν	Frisch elasticity of labor supply	3	μ_H	Mass of H type households	0.1
ρ	Persistence of productivity process	0.92	ρ_z	Firm productivity autocorrelation	0.9
σ_ϵ	Standard dev. of productivity process	0.12	$\widetilde{\alpha}$	Private firm returns to scale	0.99
λ	Public firm exit probability	0.10	$\widetilde{\mu}_e$	Mass of entrants	0.1527

Panel (b): internally calibrated parameters

Parameter and description		Target (source)	Value	Model	Data
ψ_n	Labor disutility (public)	Labor supply share 500+ (BDS)	1.2871	0.469	0.469
$\widetilde{\psi}_n$	Labor disutility (private)	Labor supply share 1-499 (BDS)	1.2349	0.531	0.531
ψ_d	Deposit utility scale	Deposit share in 3rd quintile (SCF)	0.0632	0.45	0.45
η	Elasticity of deposit utility	Top 10% deposit share (SCF)	2.6096	0.22	0.22
β	Household discount factor	Mean return US stock market	0.9182	1.08	1.08
s_H	Productivity scale H vs. L	Top 10% income share	4.6324	0.346	0.346
θ	Public firm capital share	Capital depreciation rate (NIPA)	0.2191	0.06	0.06
γ	Public firm return to scale	Labor demand share 500+ (BDS)	0.9872	0.469	0.469
σ_z	Firm productivity standard dev.	Labor demand share 1-499 (BDS)	0.0315	0.531	0.531
$\widetilde{\phi}$	Private firm bank dependence	Int. margin estimate: Table 1 Col (3)	0.952	-0.133	-0.133
$\widetilde{f}_{max}$	Upper bound of fixed cost	Ext. margin estimate: Table 1 Col (4)	0.0065	-0.027	-0.027
$\widetilde{\kappa}_{max}$	Upper bound cost of going public	Share of firms 500+ (BDS)	7879	0.003	0.003
Ξ	Banking sector fixed cost	Mean of US deposit rates	0.1028	1.04	1.04

Note: Summary of calibration for the initial stationary equilibrium. Panel (a) shows the parameters we fix to standard values. Panel (b) presents the internally calibrated parameters, which match data from the SCF and the BDS in the early 1980s. This makes the model consistent with the motivating evidence in Section 2 and the empirical estimates in Section 3.

Given households' labor supply and the normalization of initial wages, we need to ensure that labor demand from public and private firms also corresponds to the targeted employment shares for each firm type. We first calibrate the capital share in public firms' production function θ to match the capital depreciation rate to the value computed from NIPA. Given this choice of the capital share, we set public firms' return to scale γ such that they demand 46.9% of total labor, while calibrating the standard deviation of firm productivity σ_z to ensure that private firms demand the remainder. The parameter in the working capital constraint $\widetilde{\phi}$ and the upper bound of the stochastic fixed cost $\widetilde{f}_{max}$ are set to precisely reproduce our empirical estimates in Table 1, for the extensive and intensive margin.[24] We set the upper bound of the

[24]What we define as extensive margin in the model captures both entry/exit, as well as the transition from private to public firms. This is consistent with the BDS data, where the employment of a firm transitioning from one bucket to another is then counted in the new bucket.

cost of going public $\widetilde{\kappa}_{max}$ to match the share of firms with more than 500 employees in the BDS data. The bank's fixed cost implies a deposit rate of 4%, consistent with its national average over the period we consider.

Specification of the main model experiment. We increase the top 10% share from 34.5% to 50.5%, matching its US-wide evolution from the early 1980s to 2015 in the Frank (2009) data (see Figure 1, panel (a)). We generate this increase through permanent lump-sum transfers between households. By changing lump-sum redistribution, we remain agnostic about the multi-faceted sources of the rise in top income shares and abstract from any *direct* relation between macroeconomic trends and top incomes. Instead, our exercise studies the effects that arise exclusively through portfolio re-allocation, our channel of interest. In an alternative experiment below, we study different drivers of rising income inequality.

The transfers net out to zero to keep ex-ante aggregate income constant, in the spirit of controlling for mean income growth in our empirical specifications. In addition to increasing lump-sum taxes on income group L and using the revenue to provide a lump-sum transfer to income group H, we also vary the amount of taxes (transfers) that low-income (high-income) agents pay (receive) within each group. This provides flexibility in calibrating the experiments to reproduce our empirical estimates in the model. Formally, $T_{i,\chi} = c_\chi \tau \frac{s_{i,\chi}^{\varphi}}{\bar{s}_\chi}$, $\bar{s}_\chi = \sum_{i=1}^{n_\chi} s_{i,\chi}^{\varphi} m_{i,\chi} / \sum_{i=1}^{n_\chi} m_{i,\chi}$, where $c_\chi = -1$ if $\chi = L$ and $c_\chi = 1$ otherwise, and $s_{i,\chi}$ is i-th level of productivity in group χ. m_χ is the mass of households with productivity $s_{i,\chi}$ and $\bar{s}_\chi$ is the mean of $s_{i,\chi}^{\varphi}$. The total amount of taxes and transfers is denoted by τ. The parameter φ captures the degree to which households with higher productivity in the low (high) group pay (receive) a larger amount of tax (transfer). Precisely replicating our empirical estimates is achieved with $\varphi = 3.5$. τ is equal to 0.0282.

Untargeted moments. In the Online Appendix, we illustrate some key economic forces of the model in partial equilibrium. This includes an analysis of marginal propensities to consume and save (MPC and MPS) out of transitory rather than permanent income (Kaplan, Moll and Violante, 2018). While the model does not target MPC and MPS, it implies an average MPC that falls into the range of estimates in the literature and generates MPC differences along the income and wealth distribution in line with previous work. The model also implies that lower-income households rely more on labor income, and that the increase in top income shares leads to an even larger increase in top wealth shares. Regarding firms, our calibration results in an average public-to-private firm employment ratio of 204, compared to 254 in the BDS data, and an average initial exit rate across all firms of around 15%, versus 10% in the data. While our calibration does not explicitly target these facts, they are reasonably consistent with the data and thus provide additional validation of the model.

6 Quantitative experiments in general equilibrium

Our empirical results suggest that rising top incomes impact job creation among different types of firms. To examine the macroeconomic and welfare consequences, our main general equilibrium model experiment raises the top 10% income share permanently by as much as it increased in the data since 1980, from 34.5% to 50.5%.

6.1 Aggregate and firm-level outcomes

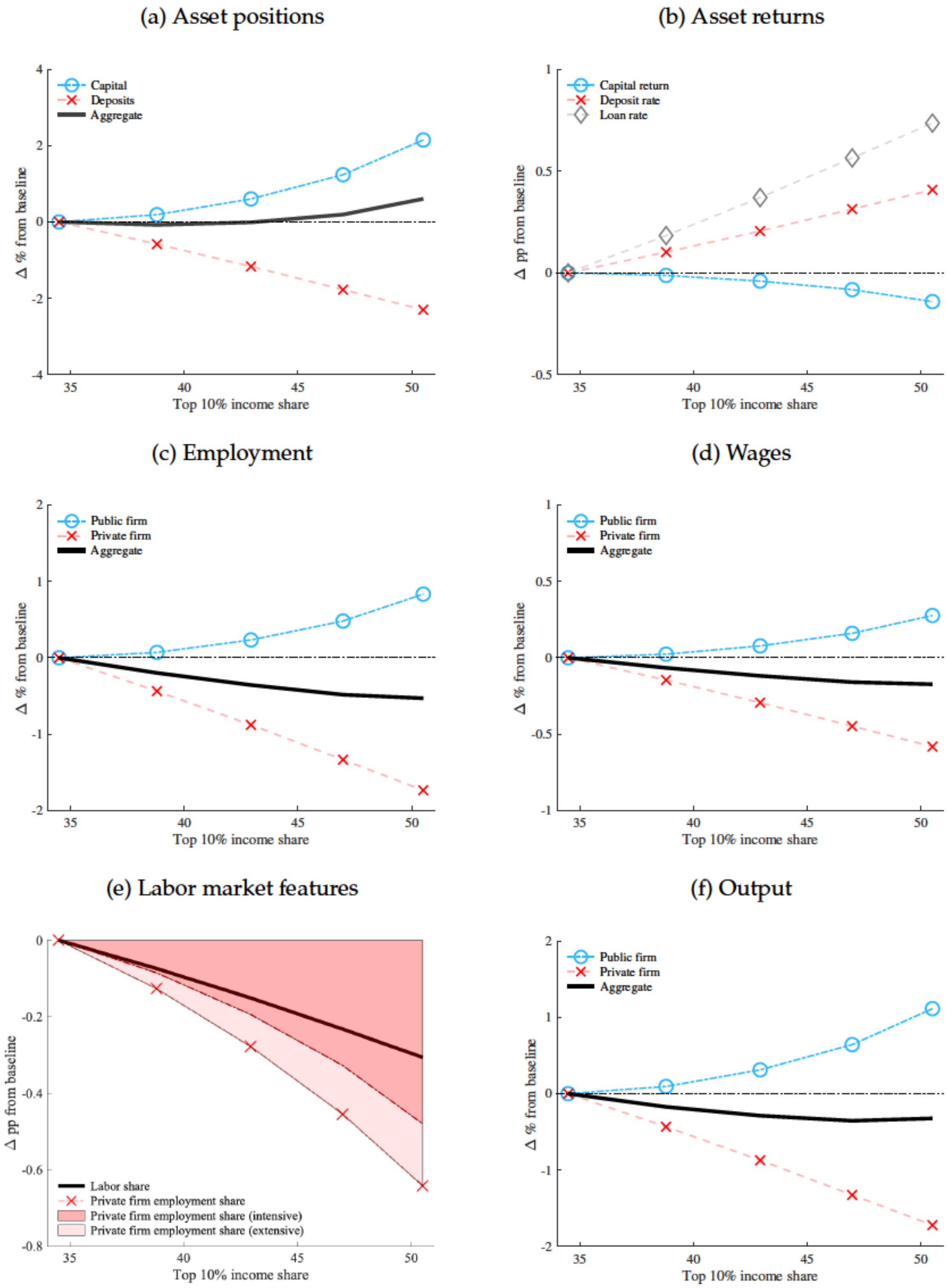
Figure 3 presents the realizations of model variables as the top 10% income share rises. Each variable is normalized to its initial level, when the top 10% income share stands at 34.5%. Panel (a) shows that, as deposits are more important for low-income than high-income households, a smaller proportion of aggregate income is saved in the form deposits when top income shares are higher. While aggregate deposits fall by more than 2%, savings flow to a larger extent into public firms' capital, leading to a 2% increase. Relatively more income accruing to high-income households slightly raises aggregate savings. This shows that total savings rates in the model can increase in permanent income, as in Dynan, Skinner and Zeldes (2004) and Straub (2019).[25]

Panel (b) shows how a higher top income share affects the returns on different assets. The return on direct firm investments, determined by public firms' marginal product of capital, falls by about 0.14 p.p. The deposit rate increases by 0.4 p.p., raising loan rates by about 0.7 p.p. due to the fixed cost in the bank's zero profit condition. Qualitatively, the latter two effects line up with the estimates in Table 2. According to Mian, Straub and Sufi (2021b), income inequality has put downward pressure on equilibrium real interest rates. Our experiment is consistent with this finding in the sense that the marginal product of public firms' capital falls. We show in addition that returns on different assets move in different directions as a consequence of higher inequality. Furthermore, note that our calibration implies that high-income households experience higher average portfolio returns for any realization of the economy's top income share, consistent with the SCF.

Our private firm comparative statics in the previous section make clear that a higher loan rate puts downward pressure on private firms' loan and labor demand. It also makes it more costly for private firms to remain in production, compared to exiting the market or becoming a public firm. Panel (c) confirms that the rise in the top income share implies almost 2% lower equilibrium employment in the private

[25] Aggregate savings increase only slightly as a consequence of matching our empirical estimates. If overall savings significantly increased due to rising income inequality, then the level of deposits would exhibit a decrease only relative to other savings, but would increase in levels. This would lead to both the deposit and loan rate to fall, which is not what we find in the data. See Online Appendix A.2 for a discussion of absolute and relative changes in our mechanism.

Figure 3: **General equilibrium consequences of rising top income shares**



Note: Selected equilibrium quantities and prices for different top 10% income shares, generated by the main experiment. We focus on aggregate outcomes as well as outcomes across different asset types, firm types and firm sizes. The calibration shown in Table 3 is used for the initial stationary equilibrium with a top 10% income share of 34.5%.

firm sector. Conversely, public firms, which now receive more capital, increase their employment by a bit less than 1%. We discuss the decline in aggregate employment below, when we interpret the behavior of aggregate output.

While not plotted in Figure 3 and not targeted by our calibration, the rise in top incomes shares also increases the relative number of public to private firms, in addition to the rise in their employment share. This is because a higher loan rate lowers the value of being a private firm and makes it more attractive to incur the cost of becoming a public firm. This increase is only about 4% of its counterpart in the data, though both in model and data the increase is very small, 0.003 p.p. and 0.08 p.p. Recall that in the model we calibrate the cost of transitioning from private to public to match the initial share of public firms of 0.35% in the data.

Panel (d) shows that wages increase in the public firm sector and fall in the private firm sector. Employment and wages move in the same direction for each labor type, reflecting that the relative labor demand effects across firm types are key for outcomes in the model's labor markets. On average, wages in the economy fall.

Panel (e) shows that the share of total employment in private firms decreases by 0.64 p.p. According to the BDS, between 1980 and 2015 the US economy experienced a decline in the share of employment in firms with less than 500 employees of 4.97 p.p. Rising top incomes, through their effect on funding conditions, can thus explain a sizeable 13% of the overall decline of that share. In line with our empirical estimates, the shaded areas highlight that around one fifth of this effect comes from the extensive margin, that is, from exit of private firms and transitions of private to public firms. In other words, a smaller set of private firms stays in production in the more unequal economy. These findings connect our mechanism to salient trends in the US economy over the last decades, such as the decrease in business dynamism and the growing importance of large firms (Decker, Haltiwanger, Jarmin and Miranda, 2016; Autor, Dorn, Katz, Patterson and Van Reenen, 2020).

The labor share falls by 0.3 p.p. as the top income share rises, as shown in panel (e). This is a consequence of public firms growing relatively larger and being more capital intensive. While we make the simplification that private firms produce with labor only, larger firms indeed have higher capital-to-labor ratios in the data (Oi and Idson, 1999). The effect of rising top income shares on the labor share aligns with another macro trend in the US and globally (Karabarbounis and Neiman, 2014). Depending on how the US labor share is computed, the literature suggests that it has fallen by 2 p.p. to 4 p.p., so our channel explains about 7.5% to 15% of this decline.

Finally, panel (f) presents the effects of higher inequality on output. As higher top income shares affect the relative funding situation across firms, public firms increase and private firms reduce production. In the aggregate, there is a modest decline in output of 0.3%, similar in magnitude to the reduction in aggregate employment. The effect of greater inequality on aggregate output is the result of two offsetting forces. On the one hand, higher top income shares lead to a larger steady state capital stock and therefore higher output, all else equal. A larger capital stock results from a given public firm getting more investment and from relatively more firms being public firms. On the other hand, a higher top income share reallocates resources across firms. If smaller, financially more constrained firms have higher marginal products, this suppresses aggregate output. The second of these effects dominates in general equilibrium for two reasons.

First, the marginal product of labor of private firms is about one sixth higher than that of public firms. Second, aggregate savings increase only modestly, which results from calibrating the model to reproduce our empirical results. Importantly, the difference in marginal products is not an apriori assumption about our model structure, but arises as a direct consequence of matching our empirical estimates in Table 1, where small firm net job creation responds relatively stronger. This difference in *marginal* products can be present even when the *level* of productivity of larger firms is higher than that of smaller firms, as some research suggests (Autor, Dorn, Katz, Patterson and Van Reenen, 2020). Indeed, in our model public firms have higher average productivity than private firms, as firms with higher productivity have a higher likelihood of becoming public.

In summary, Figure 3 shows that a higher share of income going to top earners has a substantial impact on the returns on different assets, on wages, and on firms. A sizeable fraction of the increase in the employment share of large firms as well as of the fall in the labor share over the past decades can be explained by rising top income shares. Moreover, aggregate employment and output are lower in an economy where incomes are distributed less equally. The next section will show large distributional consequences across households, with significant implications for welfare.

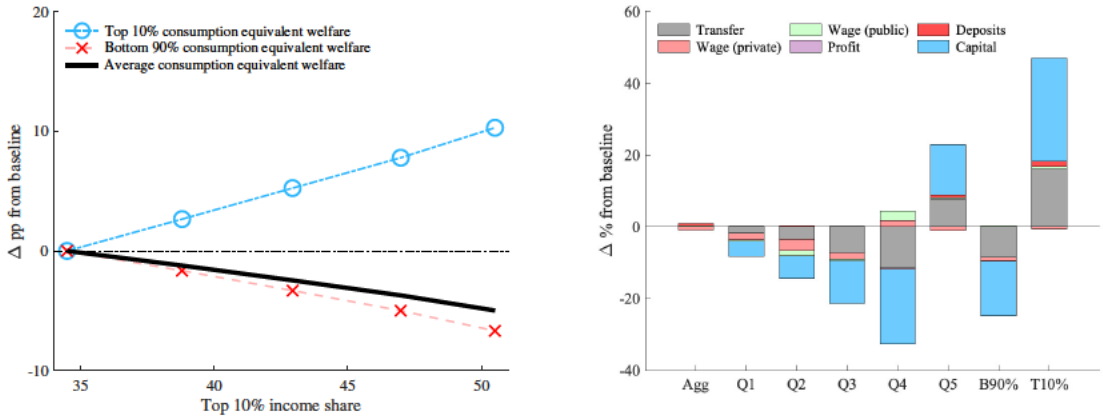
6.2 The welfare effects of rising top income shares

We compute the consumption equivalent (CE) welfare for households along the income distribution. Panel (a) of Figure 4 shows that our experiment increases welfare for the top 10% and decreases it for the bottom 90%. As the bottom 90% of households form a bigger group, with a higher marginal utility than the top 10%, the average household experiences a decline in welfare. A significant part of these patterns result from changes beyond the direct, mechanical effects of lump-sum taxes and transfers. The reason is that agents' choices, as well as wages and returns, adjust, giving rise to general equilibrium effects. Panel (b) of Figure 4 decomposes the changes in income across income groups into different sources. We consider the aggregate, the top 10% and bottom 90% of the income distribution, as well as the bottom, middle, and top quintiles, where 'Q1' ('Q5') represents the bottom (top) 20% earners. Capital income increases at the top and decreases at the bottom. Wage income declines most among households in the bottom 40% of the income distribution.

Figure 4: **Welfare effects and income decomposition**

(a) Welfare across income groups

(b) Decomposition of income changes



Note: Welfare effects (in consumption equivalents) for different top 10% income shares and decomposition of income changes between the highest at the lowest top 10% income share for different income groups. The calibration shown in Table 3 is used for the initial stationary equilibrium with a top 10% income share of 34.5%.

Welfare in a model with fixed portfolio shares. By construction, our redistribution of income benefits the top 10% and hurts the bottom 90%. To gauge the contribution of our mechanism to the welfare consequences of rising top incomes, we therefore benchmark the welfare effects in Figure 4 against their counterpart in an alternative model with fixed portfolio shares. This allows us to "net out" the direct, mechanical effects of lump-sum taxes and transfers on welfare. We can thereby assess the extent to which our channel amplifies or mitigates the welfare consequences of growing inequality for different households.

In the alternative model, we restrict households to save in a composite of deposits and capital, with shares fixed to match the average deposit share in the 1980s SCF data. The composite asset pays the weighted average of the deposit interest rate and the marginal product of capital of public firms. This 'fixed portfolio share model' is otherwise identical to our full model, and calibrated to match identical targets. The Online Appendix provides the equivalents of Figure 3 and Figure 4 for the fixed portfolio share model. Forcing capital and deposit savings to respond in a proportional way to rising top income shares implies substantially different effects, which we now discuss in comparison to the full model.

Contribution of portfolio allocation to welfare. Figure 5 shows the effects of rising inequality when households can and cannot adjust their portfolios. Panel (a) plots the change in the top 10% income share for our lump-sum transfer scheme (changes in τ as defined in Section 5). Recall that our experiment is designed to generate a change in the top 10% income share from 34.5% to 50.5% in the full model (black solid line). Imposing the same set of transfers across households in the fixed portfolio share model leads to a weaker increase in income inequality (blue circled line). When households cannot adjust their portfolios in response to income changes, the top 10% income share rises only up to around 43% in equilibrium. Our mechanism thus amplifies the effects of the initial redistribution on the top income share.

Panel (b) plots the differences in welfare between the full and the fixed portfolio share model. Positive numbers imply a relatively better welfare outcome in the full model. We find that top earners experience a stronger increase in welfare in the presence of portfolio reallocation, while households in the bottom and middle parts of the distribution face a stronger decline in welfare. Portfolio heterogeneity amplifies the positive impact of rising top income shares at the top as well as the negative impact at the bottom. The effects are economically large, amounting to differences in the order of magnitude of 1% in consumption equivalents. Ignoring the effects of income inequality on the allocation of savings thus understates the welfare effects of changes in the income distribution significantly.

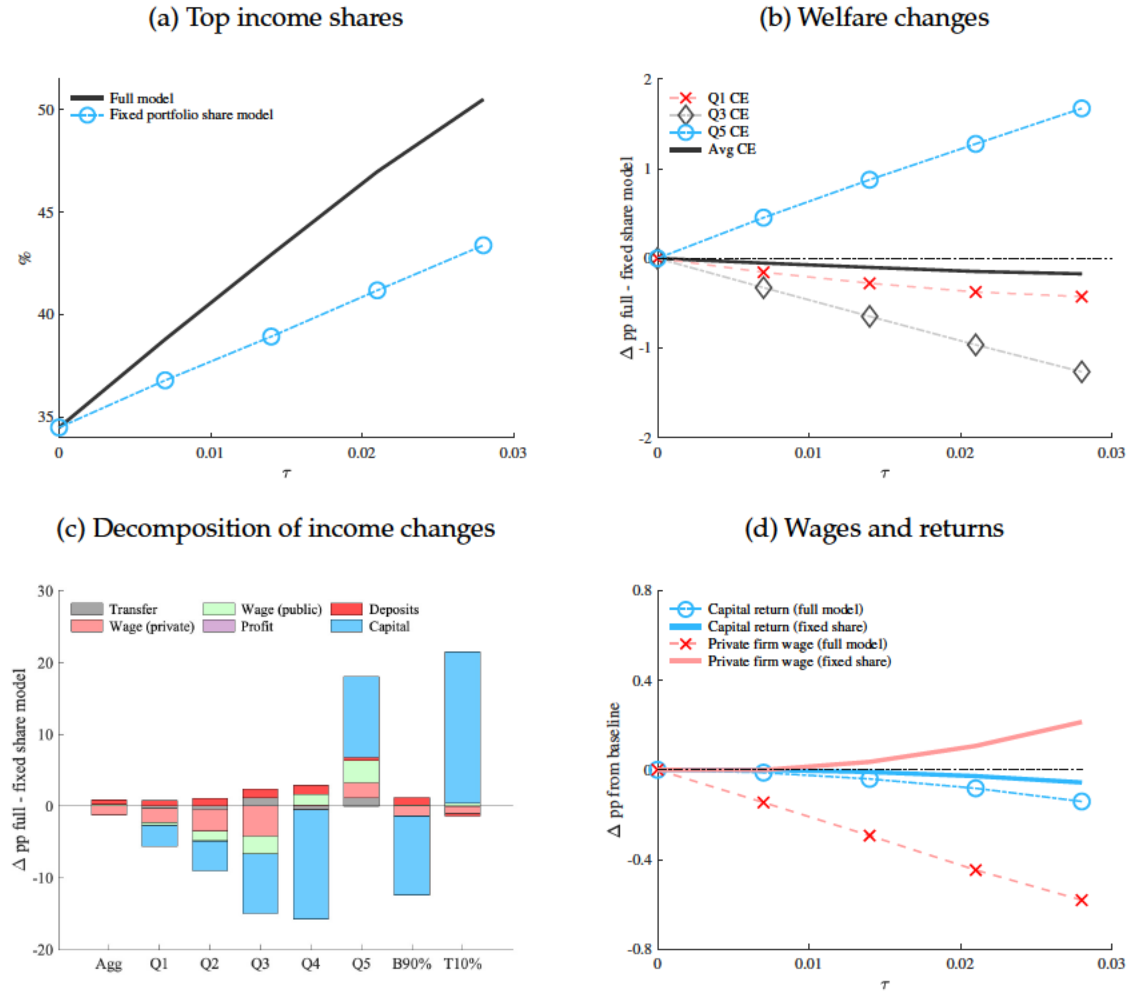
Panels (c) and (d) examine the driving forces behind these patterns. Panel (c) plots the difference in income between the full and the fixed portfolio share model across income groups, decomposed into different sources.[26] By benchmarking the experiment against an alternative model, the direct effect of exogenous transfers nets out. The figure shows that the stronger welfare impact at the top and bottom is driven by differences in both asset and labor income. We focus on the two components with the largest contribution across income groups, income from holding capital in public firms and wage income from private firms. To inform our discussion, panel (d) examines public firm returns and private firm wages in the two models.

In the full model, labor income from private firms decreases sharply, as they reduce labor demand in response to the higher loan rate. In equilibrium, private firm wages fall (see panel d). This stands in contrast to the fixed portfolio share model, in which top earners increase deposits after receiving more income, benefiting private firms through lower rates and allowing them to increase wages. Wages make up a high share of the incomes of lower income groups. In the full model, this reduction in labor income has a strong negative impact on the welfare of low income households, and while wages at public firms rise, average wages across all firms fall.

The full model also implies that capital income rises more strongly for top earners,

[26] CE welfare differences arise from different sources, including differences in income. Welfare changes in our experiments are mirrored relatively closely by income differences, and we thus focus our interpretation of the welfare results on income changes.

Figure 5: **Welfare differences between model and alternative**



Note: Welfare analysis across two different model versions. The full model is the one analyzed in Figure 3 and Figure 4. In the fixed portfolio share model (labeled 'fixed share') our main channel is shut off. The calibration shown in Table 3 is used for the initial stationary equilibrium with a top 10% income share of 34.5%.

as they shift into the higher-return investment. In turn, their capital income increases, despite a fall in the return on public firm capital (panel d). Indeed, the reduction in returns is driven by the influx of capital from high-income households. This also puts downward pressure on the capital income of lower income groups, for whom asset income is lower than with fixed portfolio shares, a pattern that is particularly pronounced in the middle of the distribution. Note that in the full model, low income households do receive higher interest rates from holding deposits. However, as panel (c) shows, differences in deposit income contribute little to overall income changes.

In summary, the link between households' portfolio adjustments and job creation of different firms amplifies the welfare impact of changes in the income distribution. Low-income individuals suffer from falling wages paid by private firms, which see a tightening in their bank funding when income inequality rises. High-income individuals benefit from higher income from capital investments in public firms that attract more funding when top income shares are higher.

6.3 Alternative inequality source, complementarities and growth

In our main experiment, we study lump-sum redistribution as a 'neutral' change in top income shares, assume that all households work at both firm types, and abstract from growth in aggregate income. While these features allow us to isolate the quantitative importance of our mechanism, our model is general enough to modify all of these aspects. We do so in an additional experiment, which demonstrates how our model can answer further questions related to income inequality and job creation.

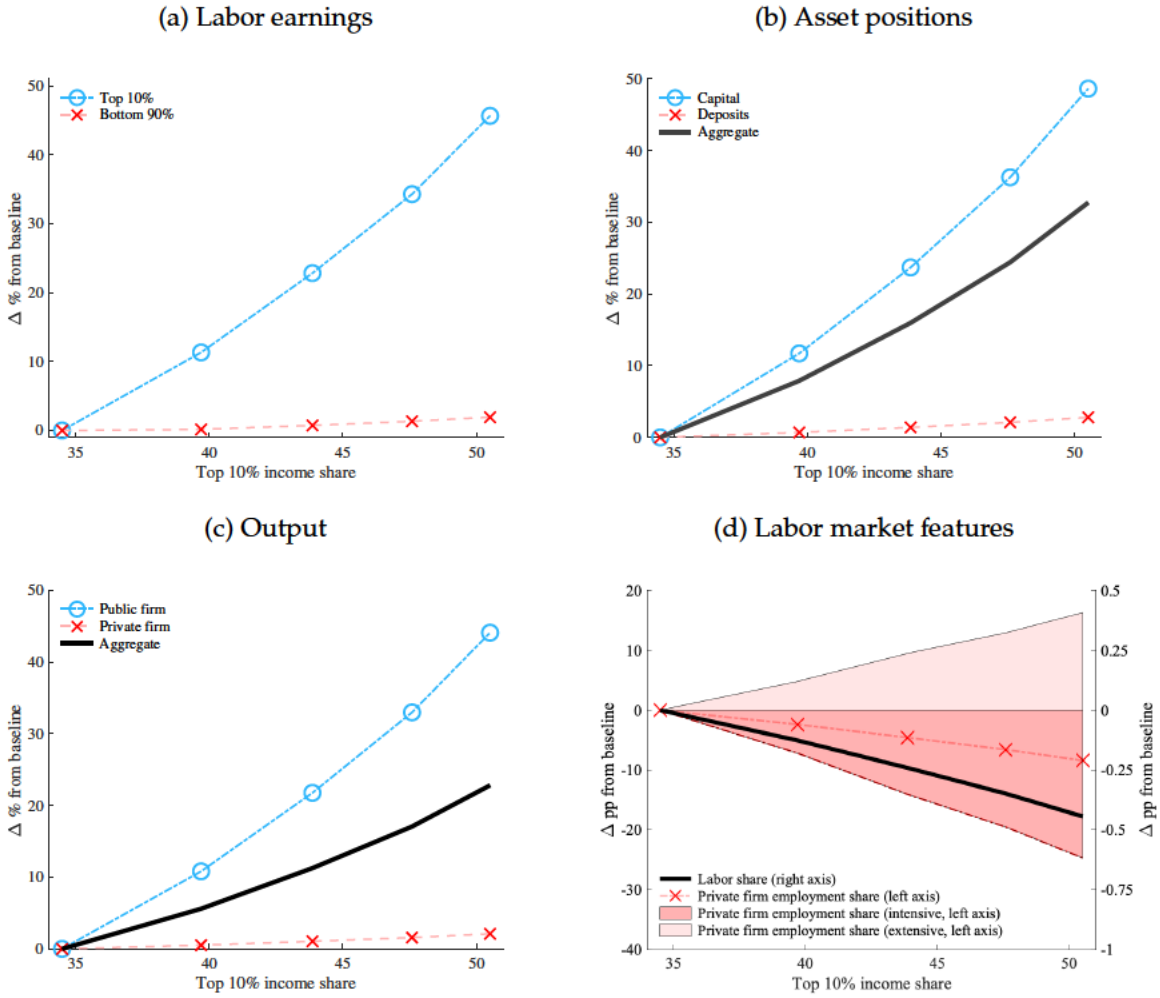
The additional experiment starts from the same initial equilibrium and calibration. We then vary top income shares by increasing the permanent component of high-income households' income processes s_H, to again raise the top 10% income share from 34.5% to 50.5%. We keep s_L the same, so this change not only generates income inequality, but also leads to higher aggregate income. Furthermore, we assume that type L households only work at private firms and type H households only at public firms, a stand-in for complementarities between high-income workers and public firm capital. This experiment is motivated by the literature on skill-biased technological change (SBTC), according to which technological change and capital-skill complementarities lead to economic growth that benefits high-skilled workers. Acemoglu (2002) provides a general discussion.[27] The Online Appendix contains further information about the setup of the experiment and additional results.

Figure 6 plots the general equilibrium realizations of key model variables. To validate that our SBTC-inspired experiment delivers results in line with the data, we compare the responses of labor earnings inequality in the model with evidence presented by Heathcote, Perri, Violante and Zhang (2023). Our experiment exactly matches the change in the top 10% share of *total* income in the US, so the implied evolution of *labor* income inequality, of particular interest in the SBTC literature, serves as an untargeted moment. Since our model has two ex-ante income types that capture the top 10% and bottom 90%, we consider the empirical facts about labor earnings in the the top and the middle of the distribution in Heathcote, Perri, Violante and Zhang (2023). Panel (a) shows that the top 10% relative to the middle 50% labor earnings share rose by a factor of 1.5 in our model experiment. In the data, it increased by a factor of 2 since 1980.

Panel (b) plots the allocation of savings. The economy experiences an increase in aggregate income, so savings in all asset types increase. As the rise in income is especially elevated at the top of the income distribution, where deposits matter less for households, savings in public firms expand strongly and increase relative to the

[27] The literature suggests also a variety of other drivers of inequality. Cowell and Van Kerm (2015) provide a survey. Our model could also be used to study specific aspects of tax systems, such as progressivity. See e.g. Heathcote, Storesletten and Violante (2017).

Figure 6: **General equilibrium effects in additional experiment**



Note: Selected equilibrium quantities and prices for different top 10% income shares, generated by the additional experiment. The additional experiment is motivated by the literature on skill-biased technological change. The calibration shown in Table 3 is used for the initial stationary equilibrium with a top 10% income share of 34.5%.

level of deposit savings. Panel (c) shows aggregate output. The size of the economy increases by about 20%. This expansion is mostly due to public firms, which receive an increasing amount of capital investment.

Panel (d) shows that higher top income shares lead to a relative decline in job creation at bank-dependent firms. The private firm employment share falls by around 8 p.p., a much larger reduction than the 0.64 p.p. decrease in our main experiment. Interestingly, the contribution of the intensive and extensive margin have different signs in this experiment. Bank-dependent firms hire fewer workers at the intensive margin, but the increase in aggregate income leads to less exit, as the value of private firms increases.

It is also noteworthy that the alternative setup leads to a stronger reduction in the economy's labor share than in the main experiment (around 0.4 p.p. instead of 0.3 p.p.), closer to what is observed in the data. This is because the degree to which public firms, which are more capital-intensive, expand relative to private firms is larger than in the main experiment, due to s_H increasing and s_L staying constant.

In sum, Figure 6 shows that the new economic mechanism we put forward in this paper has a meaningful economic impact also in a substantially different experiment. Quantitatively, the differential effect on bank-dependent relative to publicly funded firms is even stronger in the alternative experiment inspired by SBTC. Our model can generate rising income inequality in various ways, but the heterogeneity in how savings by low- and high-income household are channeled to different firms remains a central element that connects income inequality with firm job creation.

7 Conclusion

This paper proposes a novel channel that links income inequality and job creation through firms' financing conditions. Exploiting variation across US states from 1980 to 2015 and an IV strategy, we provide empirical evidence for the channel. Higher top income shares reduce job creation at bank-dependent firms, relative to other firms. Quantitative model experiments suggest that the rise in the top 10% income share over the past decades increased the employment share of large firms, decreased the labor share, and lowered aggregate output. The non-homotheticity in the allocation of savings amplifies the welfare effects of re-distributive policies. Our empirical and theoretical insights shed new light on the long-standing debate on the connection between inequality and economic outcomes. They can help to design policies addressing growing income disparities.

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A Online Appendix

The Online Appendix first provides additional background on the US banking system in Section A.1. Section A.2 expands on the distinction between shares and levels in our theoretical argument. The Appendix then provides more detail and additional tests for our instrumental variables in Section A.3. It then reports further figures and tables to support the stylized facts and empirical analysis in Section A.4. Finally, it provides additional results from the quantitative analysis in Section A.5.

A.1 The geography of the US banking system

The US banking system is, to this day, not fully deregulated. As explained in Kroszner and Strahan (2014), up until the 1970s, interstate banking was effectively banned. In consequence, the US banking system was segregated into fragmented local banking systems. From 1978 onward, more and more states liberalized entry regulations for out-of-state banks. Only in 1994, the Reigle-Neal Interstate Banking and Branching Efficiency Act stipulated complete interstate banking and branching. The removal of geographical restrictions has led to a substantial change in the structure of the banking industry. Consolidation and expansionary activities across state borders reduced the number of banks, primarily eliminating smaller institutions. However, even after de-jure deregulation in 1994, most states continued to use different policy tools to protect local banks from outside competition, as discussed in Rice and Strahan (2010). As a consequence, cross-state banking is still not fully developed, so that banks' headquarters' state plays an outsized role in their branch network – and consequently in their ability to raise deposits and engage in small business lending, as discussed in what follows.[28]

When it comes to deposits, the FDIC Summary of Deposits (SOD) data reveal that for the average bank, 98% of all deposits and 97% of all branches are located in its headquarters state (see Table OA1). Table OA2 reports the same statistics for each of the top4 banks. To account for the steady increase in size of the top-4 banks, we report average values for the pre-2000 (panel a) and post-2000 period (panel b). Even the top-4 banks raised between 34% and 76% of their deposits in branches in their headquarters state prior to 2000. After 2000, numbers are lower, especially for Bank of America, but Wells Fargo, Citi, and JP Morgan Chase still raise 31%, 41%, and 54% of their deposits in their headquarters state.

With respect to small business lending, the literature has shown that it is predominately done by smaller banks (see e.g. Berger, Klapper and Udell (2001); Berger and Black (2011) and related papers). In line with these findings, the top-4 banks have a market share of 35% in terms of total assets and in terms of total C&I lending, but they have a market share of only 19% in small business lending. Moreover, "approximately 80% of all small business loans originated [. . .] to borrowers that are less than 50 miles away from the closest branch of their bank lender" (Granja, Leuz and Rajan, 2022). And since the overwhelming majority of banks' branches are located in their headquarters state, this finding implies that the majority of small business lending is done in banks' headquarters state. Indeed, when we compute the share of CRA loans made to small businesses located in banks' headquarters state, the data show that the average bank extends 85% of its small business loans in its headquarters state.

How are deposits and loans allocated to branches and regions? For deposits, the FDIC's

[28] Beyond regulatory constraints, the literature has highlighted agency frictions within firms/banks as an impediment to geographic and organizational expansion. For example, rent-seeking divisional managers want to extract extra compensation and over-report their costs, and their ability to do so increases in distance to the headquarters (Scharfstein and Stein, 2000; Stein, 2003). For banks, Brickley, Linck and Smith Jr (2003) and Berger, Miller, Petersen, Rajan and Stein (2005) argue that distance lowers the ability of a bank's headquarters to monitor its subsidiaries and branch managers.

Table OA1: **Deposit share – non-top4 banks**

Variable	Obs	Mean	Std. Dev.
share deposits in HQs state	107782	.98	.09
share branches in HQs state	107784	.97	.11

Table OA2: **Deposit share – top4 banks**

Panel a: Pre 2000

	share deposits in HQs state	share branches in HQs state
Bank of America	.34	.26
Citi	.74	.58
JP Morgan Chase	.76	.67
Wells Fargo	.55	.45

Panel b: Post 2000

	share deposits in HQs state	share branches in HQs state
Bank of America	.09	.04
Citi	.41	.32
JP Morgan Chase	.54	.30
Wells Fargo	.31	.23

Summary of Deposits guidelines prescribe that deposits should be assigned to the branch in closest proximity to the account holder's address.[29] For small business loans, the Community Reinvestment Act data provides information on the identity of the lender (eg Bank of America or First Bank Texas) and the location of the borrower. In particular, "a small-business or small-farm loan is located in the geography where the main business facility or farm is located or where the loan proceeds otherwise will be applied, as indicated by the borrower".

A.2 Levels vs. shares

What is ultimately relevant for our theoretical mechanism is how the *level* of deposit savings changes relative to the *level* of other households savings, in response to changes in income inequality. If the level of deposits increases relative to the level of other savings, then the amount of funding available to bank-dependent firms increases relative to the amount of funding available to other firms. If so, job creation at bank-dependent firms would increase *relatively* more than at other firms. The motivating evidence in the paper is about *shares* of different savings types. In what follows, we formally proof how our evidence about deposit shares is directly connected to how the levels of different forms of savings respond to changes in income inequality.

Suppose there are two income groups, low (L) and high (H), and the behavior of all households within an income group is the same. For a given household in income group $i = \{L, H\}$, an additional dollar of income Y_i is first allocated between total savings S_i and consumption C_i, so that $Y_i = S_i + C_i$. Total savings in turn are then allocated between savings in deposits D_i and savings in other financial assets. For simplicity, we assume all other

[29]Some caveats apply. For example, for brokered deposits or foreign deposits, an institution might choose to register them with the headquarters branch, which could lead to an upward bias in the share of deposits raised in the headquarter county. In the data, brokered and foreign deposits account for less than 2.5% of total deposits for the average bank, and less than 10% when we weight by bank size.

financial assets are equity, denoted E_i. The allocation of total savings implies $S_i = D_i + E_i$.

Furthermore, suppose household behavior within in each group is described by constant shares. These shares are not constant across income groups, so they can rise or fall with income as we see in the data. We denote the savings-to-income share of income group i as $s_i = \frac{S_i}{Y_i}$ and the deposit-to-savings share as $\delta_i = \frac{D_i}{S_i}$. Together, these shares mechanically imply a deposit-to-income share $d_i = \frac{D_i}{Y_i} = s_i\delta_i$. The same is true for equity shares, where $e_i = s_i\epsilon_i$ is the equity-to-incomes share, which depends on the savings-to-income share s_i and the equity-to-savings share $\epsilon_i = \frac{E_i}{S_i}$. With two types of savings, the savings shares add up to one, so that $\epsilon_i + \delta_i = 1$.

Our motivating evidence shows that high-income households hold a smaller share of their financial savings in deposits and a higher share in other investments, relative to low income households, i.e. $\delta_H < \delta_L$. Based on this evidence, our hypothesis states that if income inequality rises ($\frac{Y_H}{Y_L}$ increases), then the level of total deposits ($D_L + D_H$) falls relative to the level of total equity ($E_L + E_H$) in the economy. It does not require total deposits to fall in absolute terms.

A key question is whether it necessarily follows from $\delta_L > \delta_H$ that when $\frac{Y_H}{Y_L} \uparrow$ then $\frac{D_L+D_H}{E_L+E_H} \downarrow$. Importantly, it has been shown in other research that high-income households save a larger share of their income in savings of any type, that is, $s_L < s_H$. Nevertheless, the hypothesis $\frac{Y_H}{Y_L} \uparrow \Rightarrow \frac{D_L+D_H}{E_L+E_H} \downarrow$ holds irrespective of the relative size of s_L and s_H. To proof this, we re-write the total amount of deposits relative to the total amount of equity as follows

$$\frac{D_L + D_H}{E_L + E_H} = \frac{d_L Y_L + d_H Y_H}{e_L Y_L + e_H Y_H} = \frac{d_L + d_H \frac{Y_H}{Y_L}}{e_L + e_H \frac{Y_H}{Y_L}}. \tag{18}$$

We can now differentiate the last expression with respect to income inequality $\frac{Y_H}{Y_L}$. The sign of that derivative tells us how total deposits to total equity investments respond to higher income inequality. Denote $\frac{Y_H}{Y_L} = y$.

$$\frac{\partial}{\partial y}\left\{\frac{d_L + d_H y}{e_L + e_H y}\right\} = \frac{d_H(e_L + e_H y) - (d_L + d_H y)e_H}{(e_L + e_H y)^2}. \tag{19}$$

This derivative is negative if $d_H(e_L + e_H y) - (d_L + d_H y)e_H < 0$. Rearranging this condition using relationships between different shares yields

$$\begin{aligned}
d_H(e_L + e_H y) - (d_L + d_H y)e_H &< 0 && (20)\\
d_H e_L + d_H e_H y - d_L e_H - d_H e_H y &< 0 && (21)\\
d_H e_L - d_L e_H &< 0 && (22)\\
\delta_H s_H \epsilon_L s_L - \delta_L s_L \epsilon_H s_H &< 0 && (23)\\
\delta_H \epsilon_L - \delta_L \epsilon_H &< 0 && (24)\\
\delta_H(1-\delta_L) - \delta_L(1-\delta_H) &< 0 && (25)\\
\frac{\delta_H}{1-\delta_H} &< \frac{\delta_L}{1-\delta_L}, && (26)
\end{aligned}$$

where (22) and (23) are equivalent because $d_i = \delta_i s_i$ and $e_i = \epsilon_i s_i$. Between (23) and (24) we divide by $s_H s_L > 0$. Inequality (26) holds if $\delta_L > \delta_H$, i.e. if low-income households hold a relatively higher share of their savings in deposits than high-income households. Importantly, this is true for all total savings shares $s_L, s_H > 0$. Even if $s_L < s_H$, i.e. if poor households have lower savings rates than rich ones, the condition $\delta_L > \delta_H$ suffices for $\frac{Y_H}{Y_L} \uparrow$

to lead to $\frac{D_L+D_H}{E_L+E_H} \downarrow$.

Note that our argument does not need to be true for the amount of deposits alone, but for the ratio of deposits to other financial assets. If relatively more income accrues to high-income earners, the fact that they generally save more would increase the level of deposits in the economy. At the same time, since high-income earners *also* increase the level of other savings, and do so by relatively more, the *relative* level of deposits will fall – leading to a *relative* decline in job creation by small firms.

A.3 Instrumental variable strategy

We develop two complementary instrumental variables (IV) for the top income share. Both IVs exploit variation in top income shares across US states and over time. The first IV combines the initial top income share in each state with the national evolution in top income shares over time. The second instrument consists of a Bartik IV research design based on the pre-determined industrial composition within each state. We leverage the fact that earnings dynamics in a small number of 4-digit NAICS industries account for most of the rise in US income inequality (Haltiwanger, Hyatt and Spletzer, 2024), and construct a shift-share instrument using the industries' beginning-of-period employment shares in each state, interacted with the nationwide employment evolution in these industries. For both IVs, this section explains their construction and presents evidence in favor of their validity and relevance.

First IV: pre-determined top income shares. Our first instrument is constructed as follows. We first predict the evolution in state-level top 10% income shares with each state's 1970 top 10% income share interacted with the national evolution in the top 10% income share. We then use the predicted evolution in the top income share as an instrument for the actual evolution in the 1980 to 2015 period. Specifically, we compute the 'leave-one-out' national trend in top income shares by excluding each respective state from the nationwide evolution used to adjust initial income shares in that state:

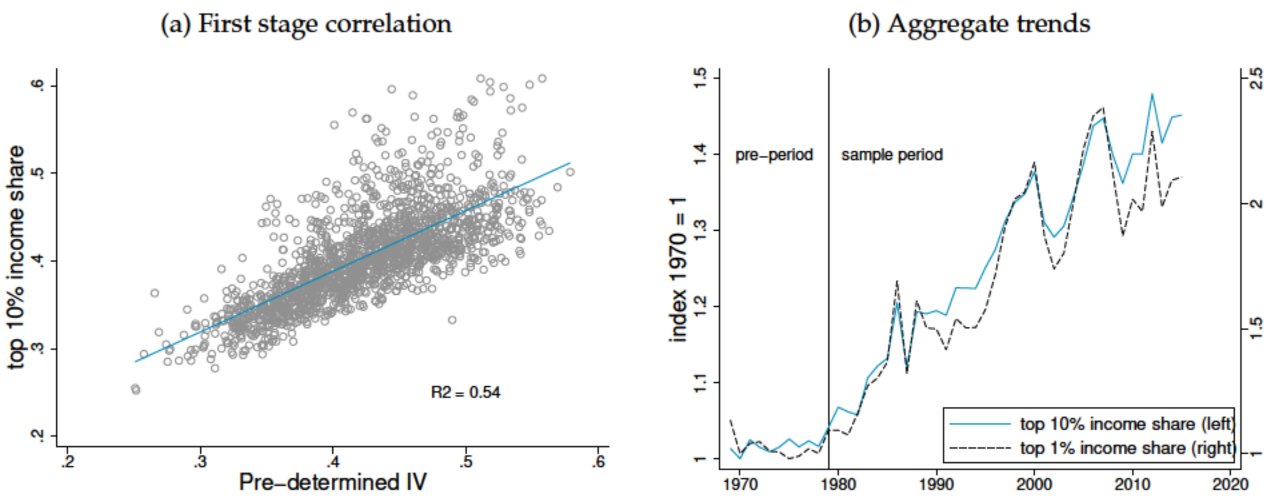
$$top\ \widehat{10\%\ share}_{s,t} = top\ 10\%\ share_{s,1970} \times \frac{1}{S}\sum_{j\neq s}^{S} top\ 10\%\ share_{j,t}. \tag{27}$$

For example, California's top income share in 1970 equaled 31% and is subsequently adjusted with the average evolution of top income shares in all states except California between 1970 and 2015. Since this IV relies on the same data as the actual top income shares (Frank, 2009), we can construct instrumental variables for both the top 10% and top 1% income share for the full sample period (1980–2015) and all states.

Figure OA1, panel (a), shows a strong and highly significant positive relation between actual and predicted state-level top 10% income shares. The coefficient estimate for the regression $top\ 10\%\ share_{s,t} = \beta\ top\ \widehat{10\%\ share}_{s,t} + \varepsilon_{s,t}$ at the state-year level is 0.69 (with $t = 44$, and $R^2 = 0.54$). For the top 1% income share, the respective values are 0.77, 45, and 0.55. The first-stage F-statistic in our preferred specification exceeds 100.

This leave-one-out approach based on pre-determined shares has several desirable properties. First, top income shares remained flat between 1970 and 1980 (see Figure OA1, panel (b)), suggesting that the initial 1970 income shares were not determined by unobservable trends also affecting the firm size distribution that were already in operation before the 1970s. This argument also implies that there is no correlation between states' initial top income shares and the initial firm size distribution. We will revisit this argument below. Further, any (unobservable) trend that affects employment and wages at small and large firms in a given state would hence need to exhibit a similar break around 1980. In addition, the leave-one-out approach implies that any such state-specific trend break would need to have happened in

Figure OA1: **Pre-determined IV – first stage and aggregate trends**



Note: Panel (a) plots actual state-level top 10% income shares on the vertical axis and predicted shares on the horizontal axis. Panel (b) presents the evolution of different top income shares over time. These remained relatively flat until 1980. Afterwards top income shares grew rapidly.

all *other* states. The instrument's construction hence mitigates the concern that unobservable state-specific shocks that affect firms of different sizes could affect the top income share in the same state.

Second, there is no systematic correlation between a state's 1970 top 10% income share and its initial firm size distribution; nor between the initial firm size distribution and its evolution over time. Suppose that states with initially more large firms also had higher income inequality in 1970 because of large firms' wage premium. If, in addition, the initial employment share of large firms is positively correlated with an increase in the employment share of large firms going forward, this could lead to a mechanical relationship between large firms' job creation and income inequality. To address this concern requires us to establish that there is *a*) no correlation between initial top income shares and the initial firm size distribution, and *b*) no correlation between the initial firm size distribution and the subsequent change in the firm size distribution.

Each panel in Figure OA2 plots the initial top 10% income share on the vertical axis against measures of the initial firm size distribution. The horizontal axis plots the initial employment share of small firms (1-499 employees) out of total state-level employment in panel (a), the initial share of small firms out of the total number of firms in panel (b), and the initial ratio of net job creation of small relative to large firms in panel (c). Each scatter point corresponds to one state. Across panels, there is no discernible correlation between initial top income shares and the firm size distribution.[30] In addition, Figure OA3 shows that there is no correlation between the initial firm size distribution (in terms of employment, number of firms, or net job creation – horizontal axes), and its change over time in the respective state (vertical axes).

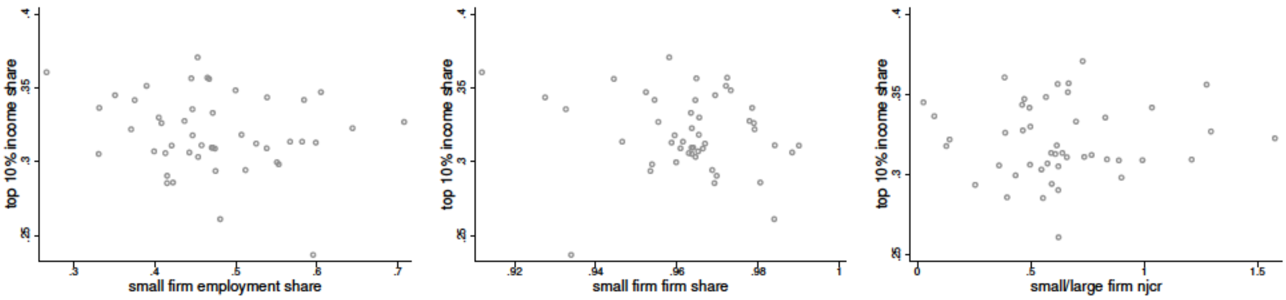
Taken together, these patterns suggest that the initial top income share is uncorrelated with the initial firm size distribution. Moreover, any firm-size specific shock affecting inequality through large firms' wage premium in a state would need to exhibit a structural break around 1980 in all other states.

As we will explain in more detail below, we perform additional tests to probe the validity of our instrument. To this end, we exclude the largest firms (i.e. those most affected by technological change) from the analysis; include state*industry*time fixed effects to control

[30] All coefficient estimates are insignificant and the adjusted R^2 ranges from 0% to 1.6%.

Figure OA2: **Pre-determined IV – firm size distribution**

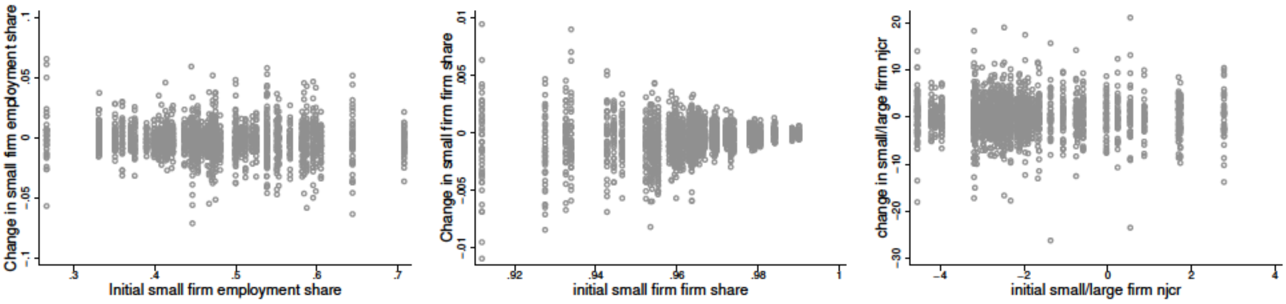
(a) employment (b) firms (c) net jcr



Note: The horizontal axis plots the initial employment share of small firms (1-499 employees) out of total state-level employment in panel (a), the initial share of small firms out of the total number of firms in panel (b), and the initial ratio of net job creation of small relative to large firms in panel (c). The vertical axis shows the initial top 10% income share in each state. Each scatter point corresponds to one state.

Figure OA3: **Initial firm size distribution and small firm developments**

(a) employment (b) firms (c) net jcr



Note: The horizontal axis plots the initial employment share of small firms (1-499 employees) out of total state-level employment in panel (a), the initial share of small firms out of the total number of firms in panel (b), and the initial ratio of net job creation of small relative to large firms in panel (c). The vertical axis shows the yearly change in each variable in each state. Each scatter point corresponds to a state-year cell.

for unobservable trends affecting firms within the same industry and state; and exclude sectors that drive the rise in inequality and account for a sizeable employment share. These tests address concerns related to the rise of superstar firms, technological change, as well as unobservable sectoral shocks.

Second IV: Bartik instrument. Our second instrument is based on the fact that income inequality is driven by a small subset of industries. Haltiwanger, Hyatt and Spletzer (2024) show that just 30 4-digit NAICS industries account for most of the rise in overall earnings inequality since 1990. Using detailed linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD), the authors show in a first step that rising between-industry dispersion explains almost three-quarters of the increase in overall earnings inequality. In a second step they show that 30 4-digit NAICS industries out of around a total of 300 account for 98% of the between-industry variance growth, and hence for most of increasing inequality.

To predict the top 10% income share in state s and year t, our shift-share IV relies on two components. First, the beginning-of-sample employment shares of those industries that explain most of the overall increase in US income inequality according to Haltiwanger, Hyatt and Spletzer (2024) ('top-30 industries' henceforth). And second, heterogeneity in the nationwide employment trends for these industries over time:

$$Bartik\ IV_{s,t} = log\left(\sum_{i\in I}\frac{emp_{s,i}}{emp_s}\times emp_{i,t}\right). \tag{28}$$

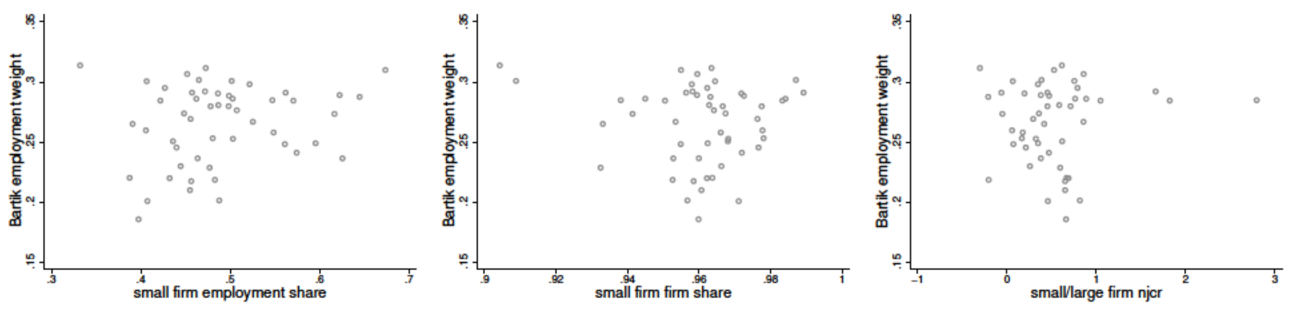
The BDS provide information on total employment for each of the top-30 4-digit industries i at the national level. To compute initial employment shares for each state-industry cell, we obtain data on the imputed County Business Patterns (CBP) from Eckert, Fort, Schott and Yang (2020). The strategy of using pre-determined, time-invariant employment shares and trends in national industry-wide employment to address reverse causality follows a well-established literature, including Autor, Dorn and Hanson (2013) and Acemoglu and Restrepo (2020).

It is important to note that the Bartik IV has two limitations. First, the analysis in Haltiwanger, Hyatt and Spletzer (2024) on LEHD data is from 1990 onward. We hence cannot construct the Bartik IV for our full sample period without making the assumptions that the same 30 industries drive inequality before 1990. Second, unlike the IV based on pre-determined shares, the Bartik IV approach does not allow us to construct separate instruments for the top 10% and top 1% income share.

A regression at the state-year level of the top 10% income share on our Bartik instrument yields $t = 16, R^2 = 0.17$, indicating a strong and positive correlation between the two variables. Similar to our IV based on pre-determined income shares, we verify that the initial employment share of the top-30 industries in a state is uncorrelated with the initial firm size distribution. In Figure OA4 we plot the employment share of the top-30 industries in a given state on the vertical axis in each panel. The horizontal axes in panels (a), (b), and (c) plot the initial share of small firms out of total employment, the total number of firms, and net job creation. Across the different measures, there is no systematic correlation between initial employment shares and the firm size distribution. It is hence unlikely that firm-specific shocks that vary systematically across states explain the initial footprint of the top-30 industries and the initial level of top income shares.

Figure OA4: **Bartik IV – firm size distribution**

(a) employment (b) firms (c) net jcr



Note: The horizontal axis plots the initial employment share of small firms (1-499 employees) out of total state-level employment in panel (a), the initial share of small firms out of the total number of firms in panel (b), and the initial ratio of net job creation of small relative to large firms in panel (c). The vertical axis shows the Bartik IV employment weight, i.e. $\sum_{i\in I}\frac{emp_{s,i}}{emp_s}$. Each scatter point corresponds to one state.

Recent papers discuss the potential threats to the validity of shift-share instruments (Adao, Kolesár and Morales, 2019; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022). One threat to identification is that the employment dynamics of a given industry within one state drive aggregate employment dynamics. Another concern is that the employment share of a given 4-digit industry (e.g. 5112) within states is very high, so that our Bartik IV mostly captures exposure to one industry.[31]

To address the concerns that a small number of industries may account for a large share of the identifying variation, we verify that individual top-30 industries constitute only a small share of overall employment at the industry- or state-level. First, we compute the employment share of top-30 industry i in state s out of total employment in industry i, based on CBP data. Table OA3 reports that the mean (median) employment share is just 2% (1%), with the 95^{th} and 99^{th} percentile equal to 6.7% and 14.8%. Second, we compute the employment share of top-30 industry i in state s out of total employment in state s (i.e. the employment weights in equation (28)). The mean (median) employment share is 1.1% (0.6%), with the 95^{th} and 99^{th} percentile equal to 4% and 7.2%.

Table OA3: **Initial employment shares**

Variable	Obs	Mean	Std. Dev.	P1	P5	P50	P95	P99
emp share of s-i cell in i	1528	.02	.031	0	.001	.01	.067	.148
emp share of s-i cell in s	1528	.011	.015	0	0	.006	.04	.072

The fact that the vast majority of top-30 industries accounts only for a small share of aggregate industry- or state-level employment dispels concerns that our Bartik IV is mostly driven by variation in just one or two industries with a large local footprint.

Testing the validity of the instruments. An interesting finding in Haltiwanger, Hyatt and Spletzer (2024) is that the top-30 industries exhibit a strong increase in the share of employment at firms with more than 10,000 employees. And among the high paying industries these mega firms experience a substantial relative increase in earnings. The rise of mega firms, which could be due to firm-size specific shocks that affect some states more than others (such as globalization or technological change (Autor, Dorn, Katz, Patterson and Van Reenen, 2020)), could also bias our estimates of the effect of rising top income shares on job creation. To address this concern, we exclude all firms with 10,000 or more or 5,000 or more employees from the analysis.

To further mitigate the concern that shocks to individual industries drive employment and top income shares in a state, we estimate regressions at the state–sector level and exclude industries that account for a particularly large share of employment. Since our data provides a breakdown only at the 2-digit NAICS level, we first compute the average employment share of the top-30 industries at the 2-digit level. Results show that only sectors 44–45, 55, 62, and 72 exceed an employment share of 2% on average.[32] We thus estimate the following regression at the state (s)-industry (i) level, but exclude these major industries from the analysis:

$$net\ jcr_{s,i,f,t} = \beta\ top\ 10\%\ income\ share_{s,t-1} \times small\ firm_f + \theta_{s,f} + \tau_{s,t} + \epsilon_{s,i,f,t}. \tag{29}$$

We instrument $top\ 10\%\ income\ share_{s,t-1}$ with the respective IV.

Any unobservable shock that affects employment at small and large firms in sectors 44–45, 55, 62, and 72 will still affect our Bartik instrument (as we use all industries in its construction), but can no longer affect our coefficient estimates through a direct effect on employment

[31]For example, suppose that high-paying industry Software Publishing (5112) employs half the workforce in California. Then an increase in its overall employment would likely not only affect income dynamics in California, but have direct effects on overall employment among large and small firms in that sector and hence in California, too.

[32]Excluding these industry codes reduces the aggregate employment share of top-30 industries in the average state from 26% to 9%.

in these industries, since we exclude them from the analysis. An additional benefit of variation at the sector level is that we can compare regressions with state*year fixed effects to those with state*sector*year fixed effects. These fixed effects that absorb any common trends that affect firms within an industry in each state differentially. These include changes in industry concentration, import competition, or technological change. In these saturated specifications, any unobservable factor that could simultaneously drive job creation and top income shares would need to affect small and large firms within the same state and industry differently.

Table OA4, panels (a) and (b) report results for the IV based on pre-determined top income shares and the Bartik IV. In each table, column (1) reports our baseline estimate at the state-firm size-year level. Columns (2) and (3) exclude firms with 10,000 or more and 5,000 or more employees from the analysis. Column (4) reports the baseline estimate at the state-sector-firm size-year level, while column (5) adds state*industry*year fixed effects, and column (6) drops all sectors that represent a significant share of employment among the top-30 industries. Across specifications, top incomes have a strong negative effect on the net job creation rate of small firms, relative to large firms.

Table OA4: **Rising top incomes and job creation – tests**

Panel (a): Pre-determined IV

VARIABLES	(1) baseline net JCR	(2) <10k net JCR	(3) <5k net JCR	(4) baseline net JCR	(5) FE net JCR	(6) FE drop i net JCR
top 10% × small firm (1-499)	-0.161***	-0.149***	-0.138***	-0.213***	-0.225***	-0.258***
	(0.022)	(0.023)	(0.023)	(0.022)	(0.023)	(0.026)
Observations	16,435	14,790	13,148	192,968	192,968	142,945
State*Size FE	✓	✓	✓	✓	✓	✓
State*Year FE	✓	✓	✓	✓	-	-
State*Industry*Year FE	-	-	-	-	✓	✓

Panel (b): Bartik IV

VARIABLES	(1) baseline net JCR	(2) <10k net JCR	(3) <5k net JCR	(4) baseline net JCR	(5) FE net JCR	(6) FE drop i net JCR
top 10% × small firm (1-499)	-0.108***	-0.089***	-0.083***	-0.146***	-0.139***	-0.142***
	(0.024)	(0.026)	(0.025)	(0.029)	(0.028)	(0.033)
Observations	12,218	10,996	9,774	146,266	146,266	108,376
State*Size FE	✓	✓	✓	✓	✓	✓
State*Year FE	✓	✓	✓	✓	-	-
State*Industry*Year FE	-	-	-	-	✓	✓

Note: This table reports results from regression (1) at the state-firm size-year level in columns (1)–(3) and at the state-industry-firm size-year level in columns (4)–(6). The dependent variable is the net job creation rate. The variable *top 10% income share* denotes the income share that accrues to the top 10% in state *s*, lagged by one period, and instrumented with the IV based on pre-determined income shares in panel (a) and the Bartik IV in panel (b). The variable *small firm* is a dummy with a value of one for the group of firms with 1 to 499 employees. Standard errors are clustered at the state level. The first-stage F-statistic exceeds 100 in every column. *** p<0.01, ** p<0.05, * p<0.1.

A.4 Further figures and tables for the empirical analysis

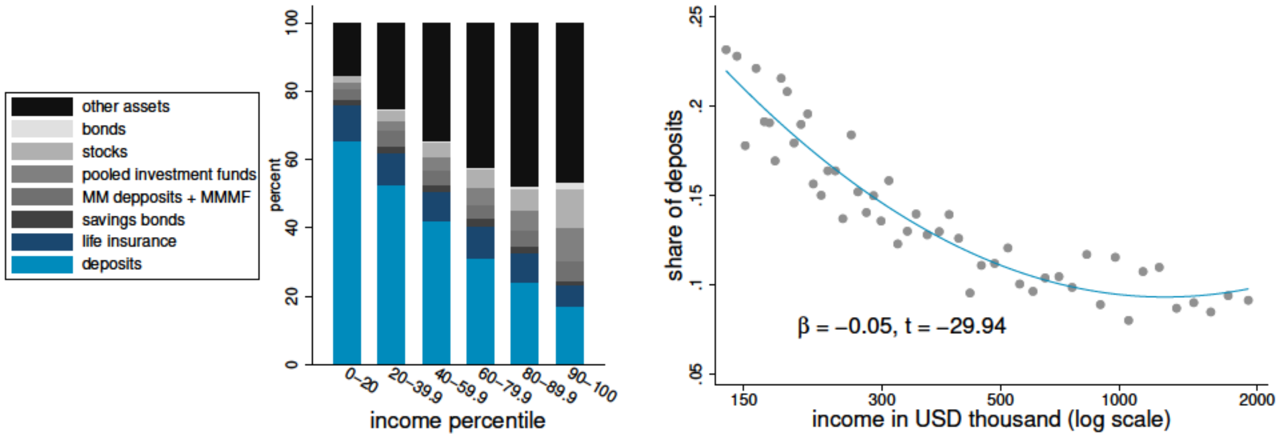
Figure OA5 provides details on the financial asset composition by household income.
Figure OA6, panels (a) and (b) provide direct evidence on household's liquidity needs by income. Panel (c) plots the *level* of deposit holdings against income and reveals a log-linear relationship. While high-income households hold relatively fewer deposits, the absolute amount of deposits increases with income.
Figure OA7 shows aggregate trends in deposits, loans, bonds, and equities.
Figure OA8 panel (a) shows funding sources for US banks, with observations weighted by total bank capital. Panel (b) presents the distribution of the share of banks' deposits and small business lending held outside banks' HQ state. 2% of banks hold more than 10% of their deposits in branches outside their headquarters state. Less than one-quarter of banks grant more than 25% of their CRA loans outside their headquarters state.
Table OA5 provides summary statistics for our main variables at the state and bank level, while panel (c) provides summary statistics for the SCF data.
Table OA6 provides additional tests to address alternative explanations for the link between top income shares and job creation along the firm size distribution. First, we investigate whether the relationship could be explained by the collateral channel: rising top income shares could be correlated with local house prices, and small and young firms rely relatively more on housing collateral to access credit (Chaney, Sraer and Thesmar, 2012; Adelino, Schoar and Severino, 2015). Columns (1) and (2) show that our results remain unaffected when we directly control for the differential effect of the growth of house prices on small and large firms. They also remain near-identical when we exclude states that experienced a housing boom, or the years of the Great recession and subsequent collapse in house prices. Venture capital is an important source of financing for startups and could possibly substitute for the decline in bank lending to small firms. Columns (3) and (4) show that when we exclude states that account for the majority of venture capital funding or directly control for the amount of venture capital invested at the state-level, our results remain unaffected. Further, column (5) shows that controlling for state-level spending on education does not affect our results. The fact that educational expenses do not explain our findings ensures that our channel is distinct from Braggion, Dwarkasing and Ongena (2021), who emphasize the importance of public goods for entrepreneurship. Note that the coefficient on the interaction term of education expenditure and the small firm dummy is positive, consistent with Braggion, Dwarkasing and Ongena (2021).
Table OA7 moves to state-industry-firm size-year level regressions. This has the advantages that, relative to equation (1), we now can control for time-varying confounding factors at the state-industry level through granular state*industry*year fixed effects ($\tau_{s,i,t}$). These absorb any differential effect that industry-wide changes could have in different states. Column (1) confirms that a rising top income share reduces job creation of small firms, relative to large firms. Column (2) exploits the rich variation in the data and uses state*industry*year fixed effects instead of state*year fixed effects. The coefficient of interest remains near-identical in terms of sign, size and significance to column (1), indicating that unobservable trends that affect industries differentially within each state do not explain our findings. Columns (3)–(6) show results for tradable and non-tradable industries. Excluding non-tradable industries addresses the concern that rising top incomes induce changes in the local demand for good, which good affect the local industrial structure.
Table OA8 shows results for the main regression with alternative outcome variables.
Table OA9 provides further robustness tests at the state-year level.
Table OA10 provides further robustness tests at the state-industry-year level. It shows that rising top incomes affect job creation in bank-dependent industries by more both along the intensive and extensive margin.

Table OA11 provides the OLS results corresponding to our main regression, while Table OA12 reports regressions where we instrument the top 10%/1% income share with both the pre-determined share IV and the Bartik IV.
Table OA13 shows that the share of deposits in total financial assets declines in income, even after controlling for an extensive set of household characteristics.
Table OA14 provides additional evidence on bank deposits and loans by bank size.
Table OA15 shows the direct link between state-level deposits and job creation by small and large firms.

Figure OA5: **More details on financial asset composition by income**

(a) Financial assets across income groups

(b) Deposit share by income within top 10%



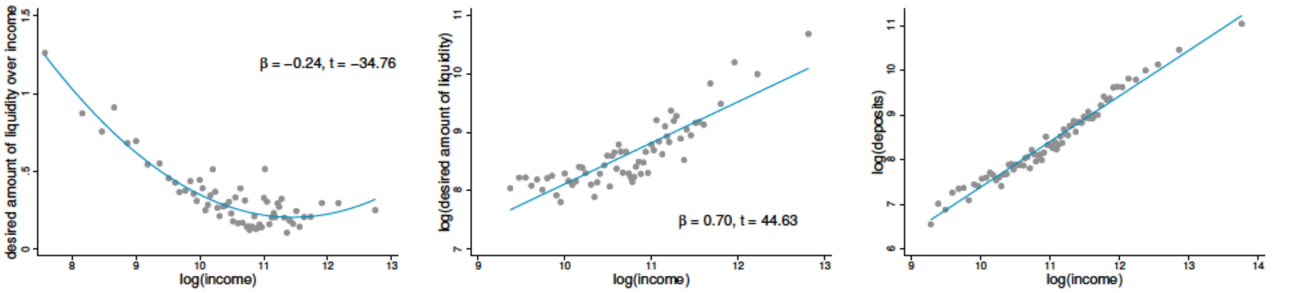
Note: Panel (a) provides a breakdown of the allocation of households' financial wealth by income group. Panel (b) provides a binned scatter plot with quadratic fit of the share of deposits over total financial assets on the vertical axis and log income on the horizontal axis for households with an income above USD 150,000. Source: Survey of Consumer Finances.

Figure OA6: **Direct evidence on household's liquidity needs by income**

(a) Desired liquidity share

(b) Desired amount of liquidity

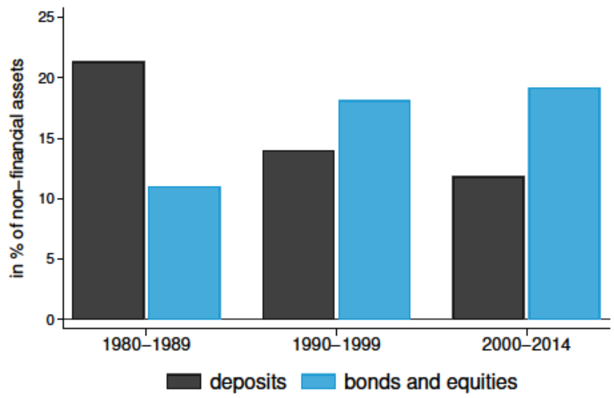
(c) Absolute deposit holdings



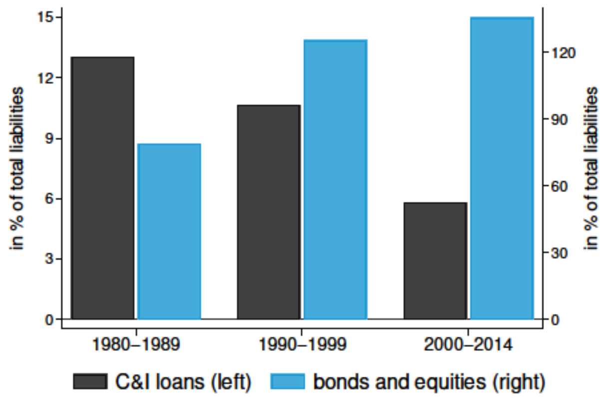
Note: Panel (a) provides a binscatter plot of the desired liquidity (defined as "About how much do you think you (and your family) need to have in savings for emergencies and other unexpected things that may come up?"), scaled by income, on the vertical axis and log income on the horizontal axis. Panel (b) shows the analogous relationship with the desired liquidity amount in logs rather than as a share of income. Panel (c) shows a binned scatter plot with linear fit of the log of total household deposits (defined as the sum of checking accounts, savings accounts, call accounts and certificates of deposit) on the vertical axis and the log of total household income on the horizontal axis. Source: 1993 Survey of Consumer Finances.

Figure OA7: **Aggregate trends in deposits, loans, bonds and equities**

(a) Household sector assets



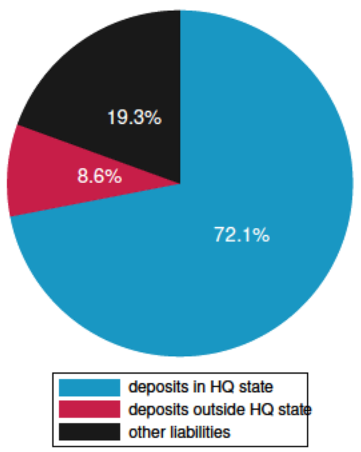
(b) Business sector liabilities



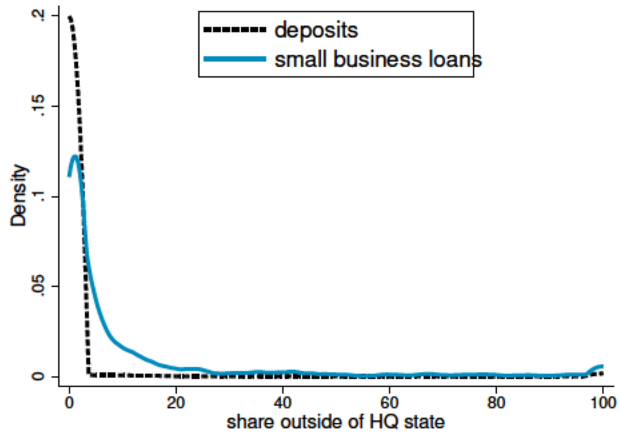
Note: Panel (a) plots deposits and bonds+equities as share of total household non-financial assets over time. Panel (b) plots C&I loans and bonds+equities as share of total non-financial corporate liabilities over time. Source: Financial Accounts of the United States.

Figure OA8: **Bank deposits and loans inside vs. outside headquarters state**

(a) Sources of bank funding



(b) Deposits and loans



Note: Panel (a) provides a breakdown of banks' total liabilities into deposits held in branches located in the banks' headquarters state, deposits held in branches located outside the banks' headquarters state, and liabilities other than deposits. Observations are weighted by total bank capital. Panel (b) shows the distribution of bank-year observations on the y-axis against the share of deposits held in branches located outside the banks' headquarters state (black dashed line) and the share of CRA small business loans originated to borrowers outside the banks' headquarters state (blue solid line) on the x-axis. Data is provided by the FDIC SOD, CRA, and US call reports.

Table OA5: **Descriptive statistics**

Panel (a): State level

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
top 10% income share	1645	.407	.054	.252	.615	.369	.403	.438
top 1% income share	1645	.15	.044	.061	.353	.119	.143	.167
Gini index	1645	.569	.047	.459	.711	.543	.567	.597
net job creation rate	1645	.013	.022	-.053	.066	.002	.018	.028
net job creation rate, extensive	1645	.007	.006	-.005	.023	.002	.006	.011
net job creation rate, intensive	1645	.006	.018	-.048	.043	-.001	.011	.019
net job creation rate, small firms	1645	.02	.032	-.129	.151	.004	.022	.038
net job creation rate, large firms	1645	.007	.029	-.153	.107	-.009	.01	.025
income per capita (in th)	1645	27.642	12.121	7.958	73.834	17.644	25.962	36.092
population (in th)	1645	5567.107	6203.077	418.493	39032.44	1340.372	3668.976	6480.591
% old population	1645	.125	.021	.029	.19	.115	.127	.137
% black population	1645	.119	.12	.002	.705	.028	.082	.163
Δ income p.c.	1645	.047	.031	-.104	.262	.031	.047	.063
unemployment rate	1645	.061	.021	.023	.154	.045	.057	.073

Panel (b): Bank level

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
log(deposits)	243674	11.093	1.317	0	16.647	10.206	10.966	11.826
deposit expense (in %)	243674	3.739	2.043	.053	13.015	2.188	3.723	5.163
log(C&I loans)	112884	9.535	1.712	0	14.787	8.421	9.446	10.575
C&I interest (in %)	112884	8.198	3.964	0	89.854	5.875	7.437	9.511
log(assets)	243674	11.437	1.373	6.878	21.423	10.515	11.289	12.163
non-interest income (in %)	243674	10.564	8.172	.327	62.203	5.628	8.679	13.023
return on assets (in %)	243674	2.137	2.6	-13.984	8.015	1.531	2.504	3.353
deposits/liabilities	243674	.946	.085	0	1	.934	.978	.99
capital/liabilities	243424	.1	.044	0	.999	.078	.092	.112

Panel (c): SCF

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
income (in USD th)	129440	83.458	310.522	0	264543	25.782	51.207	91.095
total financial assets (in USD th)	122244	223.182	1488.795	.001	1368505	3.821	28.994	134.098
% deposits (checking+saving+call+cds)	122244	.41	.4	0	1	.046	.229	.915
% direct	122244	.59	.4	0	1	.085	.771	.954
% life insurance	122244	.089	.221	0	1	0	0	.023
% savings bonds	122244	.019	.089	0	1	0	0	0
% MM deppoosits + MMMF	122244	.043	.145	0	1	0	0	0
% pooled investment funds	122244	.045	.144	0	1	0	0	0
% stocks	122244	.048	.148	0	1	0	0	0
% bonds	122244	.006	.053	0	.997	0	0	0
% other managed assets	122244	.022	.111	0	1	0	0	0
% residual assets	122244	.318	.362	0	1	0	.132	.653

Note: This table provides summary statistics for the main variables at the state and bank level in panels (a) and (b). Panel (c) shows summary statistics for main variable from the Survey of Consumer Finances. For variable definitions and details on the data sources, see the main text.

Table OA6: **Collateral, venture capital and public goods**

VARIABLES	(1) net JCR	(2) no boom states net JCR	(3) no VC net JCR	(4) net JCR	(5) edu sample net JCR
top 10% × small firm (1-499)	-0.136***	-0.143***	-0.163***	-0.292***	-0.593***
	(0.020)	(0.023)	(0.023)	(0.038)	(0.077)
house price growth × small firm (1-499)	0.100***				
	(0.015)				
log(VC deals) × small firm (1-499)				-0.003**	
				(0.001)	
education exp. × small firm (1-499)					0.025***
					(0.006)
Observations	16,435	13,291	15,035	9,450	10,120
State*Size FE	✓	✓	✓	✓	✓
State*Year FE	✓	✓	✓	✓	✓
State*Naics*Year FE	-	-	-	-	-

Note: This table reports results from regression (1) at the state-firm size-year level. The dependent variable is the net job creation rate. The variable *top* 10% *income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. In columns (1) the variable *house price growth* denotes the change in the state-level house price index, with index year 1990. Column (2) excludes states with a housing boom between 2000 and 2007. Column (3) excludes CA, MA, NY, and TX from the analysis, i.e. the states that account for the majority of venture capital (VC) funding. Column (4) directly controls for the number of VC deals in each state, interacted with the small firm dummy. Column (5) controls for state-level education expenditure as a share of GDP, interacted with the small firm dummy. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA7: **Local demand**

VARIABLES	(1) net JCR	(2) net JCR	(3) NT (narrow) net JCR	(4) T (narrow) net JCR	(5) TN (wide) net JCR	(6) T (wide) net JCR
top 10% × small firm (1-499)	-0.213***	-0.196***	-0.186***	-0.216***	-0.158***	-0.261***
	(0.022)	(0.021)	(0.021)	(0.037)	(0.021)	(0.033)
Observations	192,968	192,968	157,772	35,196	133,981	58,987
State*Size FE	✓	✓	✓	✓	✓	✓
State*Year FE	✓	✓	✓	✓	✓	✓
State*Naics FE	-	✓	✓	✓	✓	✓

Note: This table reports results from a regression at the state-industry-firm size-year level. The dependent variable is the net job creation rate. The variable *top* 10% *income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. Column (1) estimates the baseline specification at the state-industry-firm size-year level with state*size and state*time fixed effects. Column (2) adds state*industry fixed effects. Columns (3) and (5) focus on non-tradable industries, columns (4) and (6) on tradable industries. Column (3) and (4) take a narrow definition of tradable industries: only Agriculture, Forestry, Fishing and Hunting (Naics code 11), Mining, Quarrying, and Oil and Gas Extraction (21), Manufacturing (31-33), and Finance and Insurance (52) are defined as tradable industries. Column (5) and (6) additionally classify Wholesale Trade (42) and Information (51) as tradable. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA8: **Alternative outcome variables**

VARIABLES	(1) JCR	(2) births JCR	(3) cont JCR	(4) JDR	(5) deaths JDR	(6) cont JDR	(7) RAR	(8) ln(emp)	(9) ln(firms)	(10) Δ JC	(11) Δ firms
top 10% × small firm (1-499)	-0.402***	-0.189***	-0.214***	-0.240***	-0.158***	-0.085***	-0.639***	-2.696***	-2.158***		
	(0.027)	(0.014)	(0.017)	(0.017)	(0.013)	(0.011)	(0.044)	(0.301)	(0.192)		
top 10% × young (0-5)										-0.240***	-0.371***
										(0.039)	(0.032)
Observations	16,435	16,435	16,435	16,435	16,435	16,435	16,435	16,435	16,435	3,196	3,196
State*Size FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-
State*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State*Age FE	-	-	-	-	-	-	-	-	-	✓	✓

Note: This table reports results from regression (1) at the state-firm size-year level. The variable *top* 10% *income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. The variable $young\ firm$ is a dummy with a value of one for the group of firms of ages 0–5. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA9: **Robustness tests – state-year level**

VARIABLES	(1) top 1% net JCR	(2) no recession net JCR	(3) no GFC net JCR	(4) pre 2008 net JCR	(5) no boom years net JCR	(6) net JCR
top 10% × small firm (1-499)		-0.166***	-0.136***	-0.106***	-0.179***	-0.139***
		(0.023)	(0.021)	(0.026)	(0.023)	(0.031)
top 1% × small firm (1-499)	-0.201***					
	(0.025)					
Observations	16,435	14,678	15,495	12,675	12,675	16,435
State*Size FE	✓	✓	✓	✓	✓	✓
State*Year FE	✓	✓	✓	✓	✓	✓
Controls	-	-	-	-	-	× small

Note: This table reports results from regressions at the state-firm size-year level. The dependent variable is the net job creation rate. The variable *top* 10(1)% *income share* denotes the income share that accrues to the top 10% (1%) in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. Column (1) uses the top 1% income share. Column (2) excludes observations with GDP growth in the bottom decile (recessions) from the analysis. Column (3) excludes the years 2007-08 from the analysis. Column (4) only includes years prior to 2008 in the analysis. Column (5) excludes the years of the pre-GFC housing boom (2000–2007) from the analysis. Column (6) interacts the dummy $small\ firm$ with all state-level control variables. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA10: **Robustness tests – state-industry-year level**

VARIABLES	(1) low BD extensive net JCR	(2) high BD extensive net JCR	(3) low BD intensive net JCR	(4) high BD intensive net JCR
top 10% × small firm (1-499)	-0.128***	-0.163***	-0.137***	-0.176***
	(0.019)	(0.019)	(0.025)	(0.022)
Observations	60,372	63,823	60,372	63,823
State*Size FE	✓	✓	✓	✓
State*Industry*Year FE	✓	✓	✓	✓
State*Industry*Size FE	-	-	-	-
F-stat	300.8	300.8	300.8	300.8

Note: This table reports results from regression (1) at the state-industry-firm size-year level. The dependent variable is the net job creation rate along the intensive or extensive margin. The variable *top* 10% *income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable *small firm* is a dummy with a value of one for the group of firms with 1 to 499 employees. *Low/high BD* refers to industries with low/high dependence on bank lending. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA11: **Rising top incomes reduce small firm job creation – OLS results**

VARIABLES	(1) net JCR	(2) net JCR	(3) ext net JCR	(4) int net JCR	(5) net JCR	(6) low BD net JCR	(7) high BD net JCR
top 10% income share	0.031						
	(0.022)						
small firm (1-499)	0.036***						
	(0.006)						
top 10% × small firm (1-499)	-0.073***	-0.116***	-0.021**	-0.096***		-0.193***	-0.245***
	(0.014)	(0.018)	(0.008)	(0.013)		(0.030)	(0.028)
top 10% × very small firm (1-9)					-0.239***		
					(0.030)		
top 10% × small firm (10-99)					-0.066***		
					(0.021)		
top 10% × medium firm (100-499)					-0.027		
					(0.016)		
Observations	16,435	16,435	16,435	16,435	16,435	60,372	63,823
Controls	✓	-	-	-	-	-	-
State FE	✓	-	-	-	-	-	-
Year FE	✓	-	-	-	-	-	-
State*Year FE	-	✓	✓	✓	✓	-	-
State*Size FE	-	✓	✓	✓	✓	✓	✓
State*Industry*Year FE	-	-	-	-	-	✓	✓

Note: This table reports results from regression (1) at the state-firm size-year level in columns (1)–(5) and at the state-industry-firm size-year level in columns (6)–(7). The dependent variable is the net job creation rate. Columns (3) and (4) use the net job creation rate along the extensive and intensive margin as dependent variables. The variable *top* 10% *income share* denotes the income share that accrues to the top 10% in state s, lagged by one period. The variable *small firm* is a dummy with a value of one for the group of firms with 1 to 499 employees. In column (5), small firms are separated into firms with 1 to 9, 10 to 99, and 100 to 499 employees. *Low/high BD* refers to industries with low/high dependence on bank lending. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA12: **Rising top incomes and job creation – additional instrument**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			ext	int		low BD	high BD
VARIABLES	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR
top 10% income share	-0.010						
	(0.122)						
small firm (1-499)	0.060***	0.000					
	(0.009)	(0.000)					
top 10% × small firm (1-499)	-0.134***	-0.161***	-0.026**	-0.134***		-0.252***	-0.354***
	(0.021)	(0.023)	(0.011)	(0.016)		(0.034)	(0.034)
top 10% × very small firm (1-9)					-0.316***		
					(0.037)		
top 10% × small firm (10-99)					-0.107***		
					(0.030)		
top 10% × medium firm (100-499)					-0.056**		
					(0.023)		
Observations	16,435	16,435	16,435	16,435	16,435	60,372	63,823
Controls	✓	-	-	-	-	-	-
State FE	✓	-	-	-	-	-	-
Year FE	✓	-	-	-	-	-	-
State*Year FE	-	✓	✓	✓	✓	-	-
State*Size FE	-	✓	✓	✓	✓	✓	✓
State*Industry*Year FE	-	-	-	-	-	✓	✓
F-stat	56.89	165.1	165.1	165.1	106.9	282.1	275.9

Note: This table reports results from regression (1) at the state-firm size-year level in columns (1)–(5) and at the state-industry-firm size-year level in columns (6)–(7). The dependent variable is the net job creation rate. Columns (3) and (4) use the net job creation rate along the extensive and intensive margin as dependent variables. The variable *top 10% income share* denotes the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share IV and Bartik IV. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. In column (5), small firms are separated into firms with 1 to 9, 10 to 99, and 100 to 499 employees. *Low/high BD* refers to industries with low/high dependence on bank lending. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA13: **Deposit holdings and household income – variation with controls**

VARIABLES	(1) % deposits	(2) % deposits	(3) % deposits	(4) % deposits	(5) % deposits
top 10% income group	-0.269***	-0.125***	-0.125***		
	(0.003)	(0.003)	(0.003)		
income percentile 20-39.9%				-0.129***	-0.097***
				(0.005)	(0.005)
income percentile 40-59.9%				-0.236***	-0.176***
				(0.005)	(0.005)
income percentile 60-79.9%				-0.344***	-0.257***
				(0.005)	(0.005)
income percentile 80-89.9%				-0.413***	-0.304***
				(0.005)	(0.006)
income percentile 90-100%				-0.486***	-0.359***
				(0.004)	(0.006)
Observations	122,244	122,244	122,244	122,244	122,244
R-squared	0.044	0.149	0.150	0.149	0.184
Controls	-	✓	✓	-	✓
Survey wave FE	-	-	✓	-	✓

Note: This table shows that high income households hold fewer deposits as part of their total financial assets. We estimate $\%\ deposits_i = \mathbb{1}(top\ 10\%\ income\ group)_i + controls_i + \tau_t + \epsilon_i$, where $\%\ deposits_i$ is the share of deposits out total financial wealth of household i (belonging to cohort t), and dummy $\mathbb{1}(top\ 10\%\ income\ group)_i$ takes on value one if the household belongs to the top income percentile. Column (1) shows that a household in the top income group holds on average 26.9% fewer of its assets in the form of deposits. Column (2) adds an extensive set of household-level controls: age, education level, number of kids, occupation, gender, race, marriage status, home ownership, and a dummy for business ownership. The coefficient declines in size to -12.5%, but remains highly significant at the 1% level. Column (3) adds cohort fixed effects (τ_t), but the coefficient of interest remains identical in terms of sign, size, and significance. Columns (4)-(5) include dummies for each income group, where the bottom 0-20% group of households is the omitted category. Hence, all coefficients indicate the share of deposits relative to the bottom income percentiles. Column (4) uses no controls, column (5) the full set of controls. Across specifications, coefficients decline in absolute magnitude as we add controls. Yet, all coefficients are decreasing with the respective income group, and they are economically large and statistically significant at the 1% level. In column (5), the second group holds 9.7% fewer assets in the form of deposits than the bottom group, while the fourth and sixth group hold 25.7% and 35.9% fewer financial assets in the form of deposits than the bottom group. Source: Survey of Consumer Finances. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table OA14: **Call reports – bank size**

VARIABLES	(1) dep rate	(2) log(dep)	(3) CI rate	(4) log(CI)	(5) state-level net JCR	(6) state-level net JCR
top 10% income share	-51.883***	-13.331***	-174.579***	-20.017***		
	(3.308)	(0.919)	(14.092)	(2.459)		
top 10% × log(assets)	5.075***	1.352***	16.700***	1.783***		
	(0.154)	(0.033)	(0.554)	(0.087)		
top 10% × firms with 1-9 emp					0.854**	-0.396***
					(0.403)	(0.042)
very small firm (1-9) × log(median assets)					0.052***	
					(0.017)	
top 10% × very small firm (1-9) × log(median assets)					-0.109***	
					(0.038)	
very small firm (1-9) × log(banks pc)						-0.911***
						(0.194)
top 10% × very small firm (1-9) × log(banks pc)						2.361***
						(0.586)
Observations	242,651	242,651	112,393	112,393	16,086	16,086
Bank FE	✓	✓	✓	✓	-	-
Year FE	✓	✓	✓	✓	-	-
State*Size FE	-	-	-	-	✓	✓
State*Year FE	-	-	-	-	✓	✓

Note: This table reports regressions at the bank-year level in columns (1)–(4) and at the state-firm size-year level in columns (5)–(6). *top 10% income share* is the income share that accrues to the top 10% in state s, lagged by one period, and instrumented with the pre-determined share instrument. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. *** p<0.01, ** p<0.05, * p<0.1.

Table OA15: **Bank deposits and job creation**

VARIABLES	(1) net JCR	(2) net JCR	(3) net JCR	(4) larger banks net JCR	(5) smaller banks net JCR
log(deposits)	-0.011***				
	(0.003)				
small firm (1-499)	0.003***	0.003***			
	(0.001)	(0.001)			
log(deposits) × small firm	0.021***	0.021***	0.021***	0.014**	0.026***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.007)
Observations	13,335	13,335	13,335	4,349	4,617
R-squared	0.291	0.406	0.445	0.471	0.419
Controls	✓	✓	✓	✓	✓
State FE	✓	-	-	-	-
Year FE	✓	-	-	-	-
State*Year FE	-	✓	✓	✓	✓
State*Size FE	-	-	✓	✓	✓

Note: This table reports results at the state-firm size-year level. The dependent variable is the net job creation rate. Standard errors are clustered at the state level. The variable $log(deposits)$ denotes the log of total deposits in banks headquartered in state s. The variable $small\ firm$ is a dummy with a value of one for the group of firms with 1 to 499 employees. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.
*** p<0.01, ** p<0.05, * p<0.1.

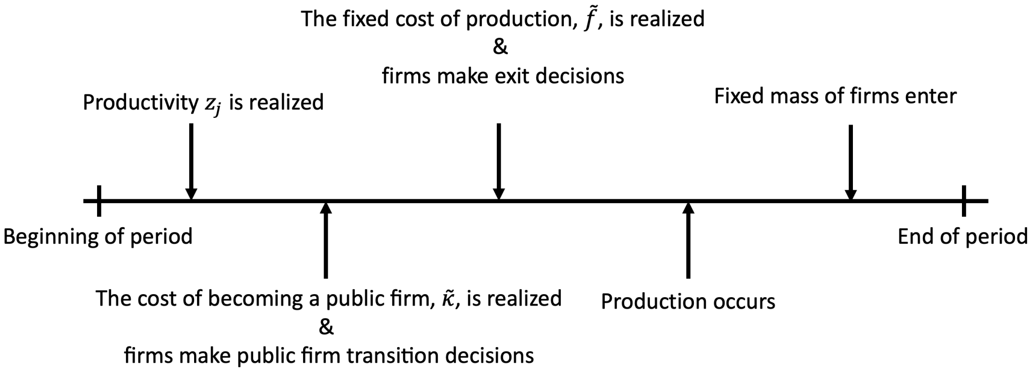
A.5 Additional details and results for structural model

This Appendix provides additional details for the structural model in Section 5.

Timeline in private firm problem

Figure OA9 provides a timeline of decisions in the private firms' problem.

Figure OA9: **Model timeline**



Law of motion for the firm distribution

Let $\mu_{f,t}$ and $\mu^p_{f,t}$ denote the distributions of private and public firms at the end of period t. As new firms enter the market at the end of each period, we have the following law of motion for the private firm distribution:

$$\mu_{f,t}(z_j) = \widetilde{\mu}_{f,t}(z_j) + \mu_e \mu_z(z_j) \tag{30}$$

with

$$\widetilde{\mu}_{f,t}(z_j) = \{1 - \widetilde{p}(z_j)\}\{1 - \widetilde{p}_{exit}(z_j)\} \int \mu_{f,t-1}(z_i) g_z(z_j|z_i) di, \tag{31}$$

where g_z is the marginal (conditonal) density of firm productivity and μ_z is the ergodic distribution of the firm productivity. $\widetilde{\mu}_{f,t}$ is the distribution of private firms that operate in the period. $\widetilde{p}_{exit}(z_{j,t}) \equiv Prob(\widetilde{f}_{j,t} > \widetilde{f}^*(z_{j,t}))$ is the probability of private firm exit and $\widetilde{p}(z_{j,t}) = Prob(\widetilde{\kappa}_{j,t} \leq \widetilde{\kappa}^*(z_{j,t}))$ is the probability of becoming a public firm. Analogously, the law of motion for public firms is given by

$$\mu^p_{f,t}(z_j) = (1 - \lambda) \int \mu^p_{f,t-1}(z_i) g_z(z_j|z_i) di + \widetilde{p}(z_j) \int \mu_{f,t-1}(z_i) g_z(z_j|z_i) di. \tag{32}$$

Market clearing conditions

There are five markets in the model: goods market, public firm labor market, private firm labor market, capital market, and loan (deposit) market. The two labor market clearing conditions are given by

$$\int N_t^*(z_j)\mu_{f,t}^p(z_j)dj = \int s_i n_{i,t} di \tag{33}$$

$$\int \widetilde{n}_t^*(z_j)\widetilde{\mu}_{f,t}(z_j)dj = \int s_i \widetilde{n}_{i,t} di, \tag{34}$$

where the left-hand side of both equations is labor demand and the right-hand side is labor supply. The capital market clearing condition is

$$\int K_{t+1}^*(z_j)\mu_{f,t}^p(z_j)dj = \int k_{i,t+1} di. \tag{35}$$

Since private firms borrow a fraction of their wage bill, aggregate loan demand can be expressed in relation to private firm employment

$$L_{t+1} = \int \widetilde{\phi}\widetilde{w}_t\widetilde{n}_t^*(z_j)\widetilde{\mu}_{f,t}(z_j)dj + \int \int_0^{\widetilde{f}^*(z_j)} x d\Phi_{\widetilde{f}}(x) \int \{1 - \widetilde{p}(z_j)\}\mu_{f,t-1}(z_i)g_z(z_j|z_i)didj. \tag{36}$$

Aggregate loans must equal aggregate deposits in the banking sector, so that

$$L_{t+1} = D_{t+1} = \int d_{i,t+1} di. \tag{37}$$

Finally, the goods market clearing condition is given by

$$\int Y_t(z_j)\mu_f^p(z_j)dj + \int \widetilde{y}_t(z_j)\widetilde{\mu}_{f,t}(z_j)dj = C_t + I_t, \tag{38}$$

where aggregate consumption and investment are $C_t = \int c_{i,t} di$ and $I_t = K_{t+1} - (1-\delta)K_t$. We always assume that $\int T_{i,t} di = 0$, i.e. that transfers net out to zero.

Stationary equilibrium definition

A stationary equilibrium is defined by a set of prices $\{R_k, R_d, w, \widetilde{w}, R_l\}$, and a set of quantities $\{c_i, n_i, \widetilde{n}_i, d_i, k_i, K, N, Y, \widetilde{y}_j, \widetilde{n}_j, \Pi_i, L, D, C, I, G, T_i\}$ that satisfy:

1. Variables $\{c_i, n_i, \widetilde{n}_i, d_i, k_i\}_{i\in[0,1]}$ maximize household i's expected discounted life-time utility (4) subject to (5), taking $\{R_d, R_k, w, \widetilde{w}, \Pi_i, T_i\}$ as given.

2. Each public firm's capital and labor demand satisfies the optimality condition (15) and (16). Public firms' output is determined by (13).

3. Each private firm j makes an exit decision, based on $\widetilde{V}(z_{j,t}, \widetilde{f}^*(z_{j,t})) = 0$ and optimal employment $\widetilde{n}_j^*$ according to (9) for a given loan rate R_l. The output of private firm j is given by (7).

4. The loan rate is determined by (17) for a given deposit rate R_d

5. The price variables $\{R_k, R_d, R_l, w, \widetilde{w}\}$ clear all markets.

Solution algorithm

1. Guess the aggregate capital stock K.

2. For a given K, guess the deposit rate R_d.

3. Guess the public firm wage w, private firm wage $\widetilde{w}$, capital rental rate R_k, and loan demand L.

4. For given wages, the rental rate of capital, and the deposit rate, compute public firms' capital and labor demand, and private firms' labor demand.

$$K^*(z_j) = \left\{ z_j \left(\frac{\theta}{R_k - 1 + \delta} \right)^{1-\gamma+\theta} \left(\frac{\gamma - \theta}{w} \right)^{\gamma-\theta} \right\}^{\frac{1}{1-\gamma}} \tag{39}$$

$$N^*(z_j) = \left(\frac{\gamma - \theta}{\theta} \right) \left(\frac{R_k - 1 + \delta}{w} \right) K^*(z_j) \tag{40}$$

$$\widetilde{n}^*(z_j) = \left[\frac{\widetilde{\alpha} z_j}{\{1 + (R_\ell - 1)\widetilde{\phi}\}\widetilde{w}} \right]^{\frac{1}{1-\widetilde{\alpha}}} \tag{41}$$

where

$$R_\ell = R_d + \frac{\Xi}{L}. \tag{42}$$

5. Do value function iteration and compute the exit probability and the probability of going public.

$$\begin{aligned} V(z_j) = {} & z_{j,t} K^*(z_j)^\theta N^*(z_j)^{\gamma-\theta} - (R_k + \delta - 1) K^*(z_j) - w N^*(z_j) \\ & + \beta_f (1 - \lambda) \int V(z_i) g_z(z_i | z_j) di \end{aligned} \tag{43}$$

$$\begin{aligned} \widetilde{V}(z_j, \widetilde{f}_j) = {} & z_j \widetilde{n}^*(z_j)^{\widetilde{\alpha}} - R_\ell \widetilde{f}_j - \{1 + \widetilde{\phi}(R_\ell - 1)\} \widetilde{w} \widetilde{n}^*(z_j) \\ & + \beta_f \int \widetilde{W}(z_i) g_z(z_i | z_j) di \end{aligned} \tag{44}$$

$$\widetilde{W}(z_j) = \widetilde{p}(z_j)\{V(z_j) - \bar{\kappa}(z_j)\} + \{1 - \widetilde{p}(z_j)\} \int_0^{\widetilde{f}^*(z_j)} \widetilde{V}(z_j, x) d\Phi_{\widetilde{f}}(x) \tag{45}$$

$$\widetilde{p}(z_j) = \int_0^{\widetilde{\kappa}^*(z_j)} d\Phi_{\widetilde{\kappa}}(x) \tag{46}$$

$$\widetilde{p}_{exit}(z_j) = \int_0^{\widetilde{f}^*(z_j)} d\Phi_{\widetilde{f}}(x). \tag{47}$$

The threshold level of each cost is pinned down by

$$\widetilde{V}(z_j, \widetilde{f}^*(z_j)) = 0 \tag{48}$$

$$V(z_j) - \widetilde{\kappa}^*(z_j) = \int_0^{\widetilde{f}^*(z_j)} \widetilde{V}(z_j, x) d\Phi_{\widetilde{f}}(x). \tag{49}$$

Note: Since the firm's value includes the expected continuation value, a firm's instantaneous profit can be negative even when it decides to continue operating. We implicitly assume that all firms are owned by a mutual fund whose shares are held by households, and this mutual fund supports any negative profits of individual firms. Assuming instead that firms exit when profits are negative does not qualitatively alter our results.

6. Compute the stationary private and public firm distribution.

$$\mu_f(z_j) = \widetilde{\mu}_f(z_j) + \mu_e \mu_z(z_j) \tag{50}$$

$$\widetilde{\mu}_f(z_j) = \{1 - \widetilde{p}(z_j)\}\{1 - \widetilde{p}_{exit}(z_j)\} \int \mu_f(z_i) g_z(z_j|z_i) di \tag{51}$$

$$\mu_f^p(z_j) = (1-\lambda) \int \mu_f^p(z_i) g_z(z_j|z_i) di + \widetilde{p}(z_j) \int \mu_f(z_i) g_z(z_j|z_i) di. \tag{52}$$

7. Check the labor market clearing conditions.

$$\int N^*(z_j) \mu_f^p(z_j) dj = \int n_i di \tag{53}$$

$$\int \widetilde{n}^*(z_j) \widetilde{\mu}_f(z_j) dj = \int \widetilde{n}_i di. \tag{54}$$

8. Check if the guess for the aggregate capital stock and loan demand coincide with the actual capital and loan demand from the firm sector.

$$K = \int K^*(z_j) \mu_f^p(z_j) dj \tag{55}$$

$$L = \int \widetilde{\phi} \widetilde{w} \widetilde{n}^*(z_j) \widetilde{\mu}_f(z_j) dj + \int \int_0^{\widetilde{f}^*(z_j)} x d\Phi_{\widetilde{f}}(x) \int \{1 - \widetilde{p}(z_j)\} \mu_f(z_i) g_z(z_j|z_i) di dj. \tag{56}$$

9. Iterate steps 3 to 8 until the labor market clears and capital and loan demand coincide with the corresponding guesses.

10. Compute the aggregate profit.

$$\begin{aligned}\Pi = \int & \{z_j K^*(z_j)^\theta N^*(z_j)^{\gamma-\theta} - wN^*(z_j) - (R_k + \delta - 1) K^*(z_j)\} \mu_f^p(z_j) dj \\ \int \int_0^{\widetilde{f}^*(z_j)} & \{z_j \widetilde{n}^*(z_j)^\alpha - \{1 + \widetilde{\phi}(R_\ell - 1)\} \widetilde{w} \widetilde{n}^* - R_\ell x\} d\Phi_{\widetilde{f}}(x) \widetilde{\mu}_f(z_j) dj \\ & - \int \int_0^{\widetilde{\kappa}^*(z_j)} x d\Phi_{\widetilde{\kappa}}(x) \mu_f(z_j) dj.\end{aligned} \tag{57}$$

11. For given $R_k, R_d, w, \widetilde{w}, \Pi, T_i$, solve the household's problem.

12. Check the market clearing condition for deposits.

$$D = \int d_i di = L \tag{58}$$

13. Repeat steps 2 to 12 until the deposit market clears.

14. Check the capital market clearing condition.

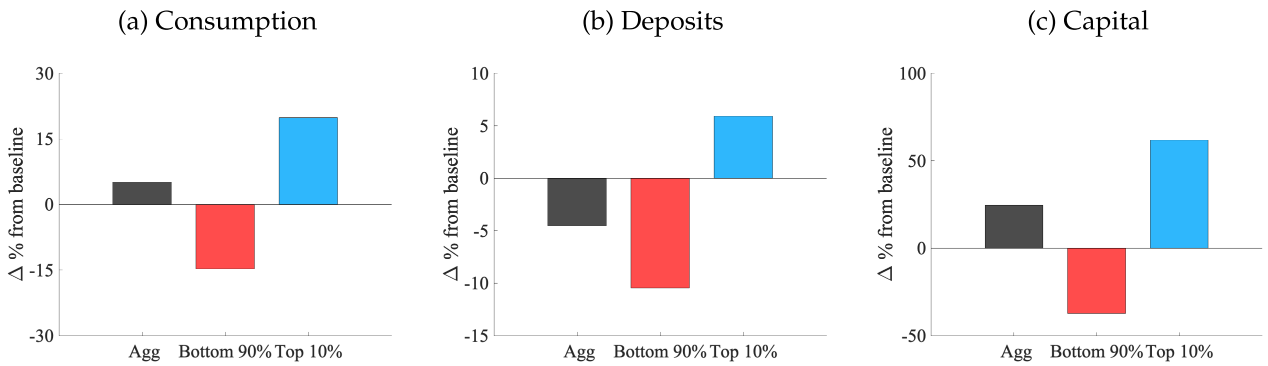
$$K = \int k_i di \tag{59}$$

15. If the market clears, the model is solved. Otherwise, update the guess for K and repeat the procedure.

Model features in partial equilibrium

While we study the model in general equilibrium in the main text, we characterize households' partial equilibrium choices holding wages and returns constant. Figure OA10 plots the responses of consumption, bank deposits, and public firms' capital to the redistribution scheme described in the main text, holding wages and returns fixed. Each panel contains the response in the aggregate, for the bottom 90%, and for the top 10% of households. We scale all responses by the initial aggregate quantity. The bottom 90% households, experiencing a fall in income, reduce consumption and savings in deposits and public firm capital. Top earners, experiencing an increase in income, consume more and save more in deposits and capital.

Figure OA10: **Consumption, savings and portfolio allocation in partial equilibrium**



Note: Summary of households' partial equilibrium responses to an income change that increases the income at the top and decreases income at the bottom. It plots the responses of consumption, bank deposits and public firm capital in the aggregate, as well as the contribution of the bottom 90% and the top 10% households. The responses are scaled by the aggregate quantity in the initial stationary equilibrium. Wages and returns are fixed.

The magnitudes of these responses differ across income groups. For lower income households, deposits make up a large share of their portfolios because they have a stronger preference for holding them. In addition, each group's income and savings make up different shares of the aggregate. The bottom 90% of households hold a larger share of overall deposits, so their reduction in deposits drives the fall in aggregate deposits. This contrasts with the rise in aggregate public firm capital, which is to a large degree held by the top 10%. The top 10% also contribute strongly to the aggregate increase in consumption. The relative magnitudes across panels imply that the partial equilibrium response in total savings (the sum of deposits and capital) is stronger than that of consumption. While Figure OA10 is instructive to understand the mechanics underlying households' choices, the size of these responses will differ in the general equilibrium experiment, where wages and returns adjust.

Discussion of MPC and MPS in the structural model

The economic mechanism we analyze in this paper operates as a trend over several decades, modeled as a *permanent* income reallocation. Therefore the patterns in Figure OA10 do not correspond to marginal propensities to consume and save (MPC and MPS) out of *transitory* income that are typically studied in the heterogeneous agent macro literature (Kaplan, Moll and Violante, 2018).

While not the focus of our paper, we examine whether our model exhibits an empirically plausible marginal propensity to consume (MPC) and marginal propensity to save (MPS), as defined in the macro literature. Specifically, we compute households' consumption and saving responses to an unexpected transitory income transfer. The size of this transitory income shock is equal to 10% of average quarterly income.

The resulting average MPC in our model is 0.11, which is on the lower end of estimates in the literature. A wide range of papers finds values between 0.1 and 0.9 for the average MPC of households in the United States and other countries.[33] A relatively low MPC in the model can be attributed to some features that the model abstracts from but that would likely result in stronger consumption responses to transitory income changes. Examples from the literature are preference heterogeneity and the presence of illiquid assets.[34] The fact that deposits in our model play the role of a necessity good further reduces households' MPC.

Table OA16 presents MPCs and MPSs along the income distribution and along the wealth distribution (in brackets). The model generates qualitatively plausible distributions. For instance, Jaspelli and Pistaferri (2014) show that households with low cash-on-hand exhibit higher MPCs than households with high cash-on-hand.[35] Similarly, in our model, low income and low wealth households have higher MPCs than high income and high wealth households, although the difference between the bottom 90% and the top 10% is modest. In the model, income and wealth are positively correlated (correlation coefficient of 0.84) and all assets are liquid. Regarding the differences in MPS across asset types, low income and low wealth households have higher MPS in deposits than high income and high wealth households, leading to higher deposit shares among lower-income households.

Table OA16: **MPC and MPS along the income [wealth] distribution**

	MPC	MPS	
		deposits	capital
Q1	0.15 [0.13]	0.48 [0.37]	0.36 [0.50]
Q2	0.11 [0.08]	0.29 [0.09]	0.60 [0.83]
Q3	0.09 [0.08]	0.14 [0.08]	0.78 [0.84]
Q4	0.08 [0.08]	0.08 [0.07]	0.84 [0.85]
Q5	0.09 [0.08]	0.10 [0.06]	0.80 [0.86]
Bottom 90%	0.11 [0.11]	0.23 [0.23]	0.66 [0.66]
Top 10%	0.10 [0.10]	0.12 [0.05]	0.78 [0.87]
Average	0.10 [0.10]	0.22 [0.22]	0.67 [0.67]

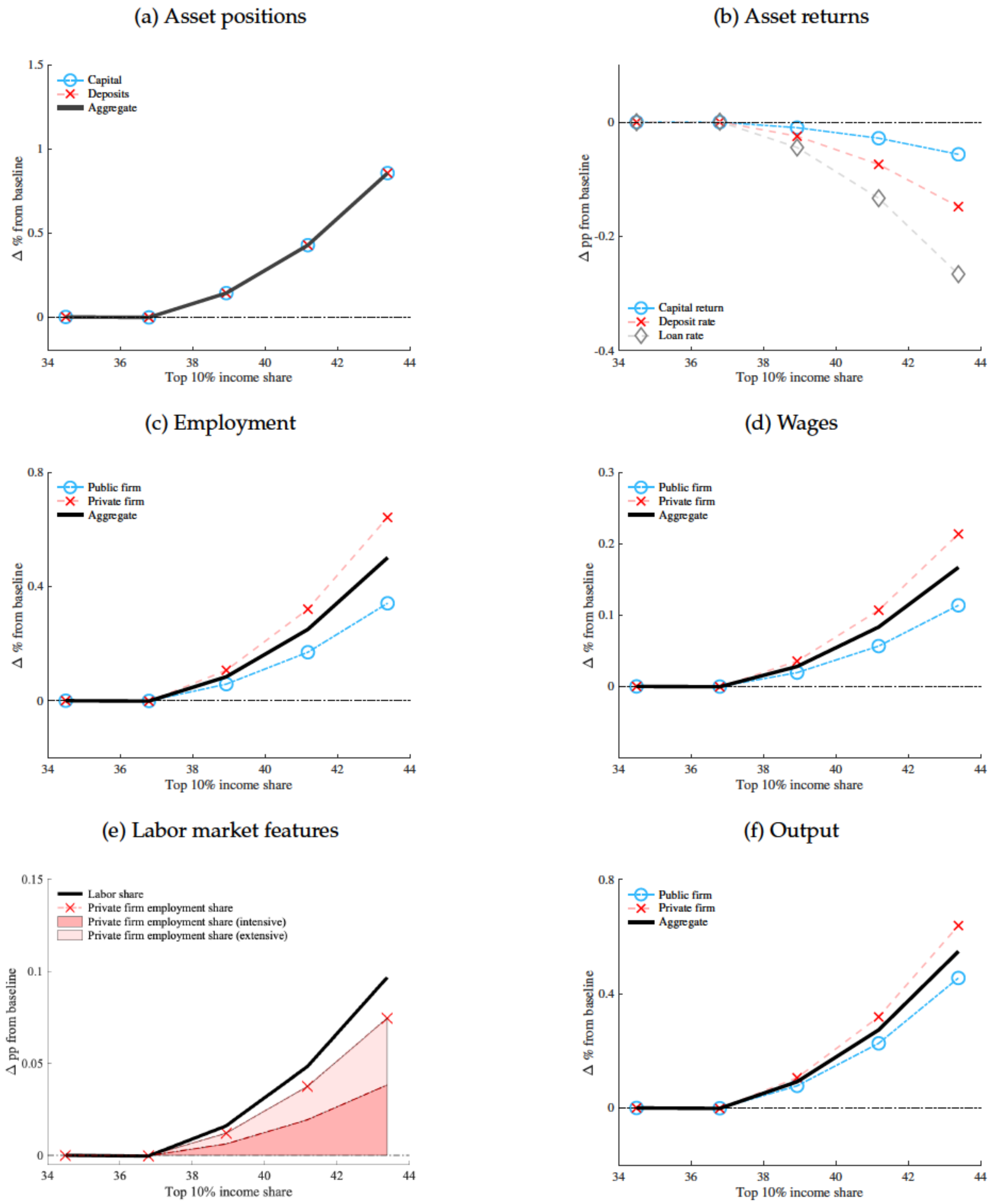
[33] Parker (1999) and Parker et al. (2013) report estimates ranging from 0.12 to 0.3 for the average quarterly MPC on non-durable goods. Shapiro and Slemrod (2009) and Sham et al. (2010) find that households spend one-third of stimulus checks in a year. Jaspelli and Pistaferri (2014) report a relatively high value of the average MPC, 0.48, using survey results on Italian households. Also, Souleles (2002) finds substantially higher values for the average annual MPC, ranging from 0.6 to 0.9, on non-durable goods.

[34] Carrol et al. (2017) show that modest preference heterogeneity, i.e. the existence of impatient households, can increase the average MPC in macro models with heterogeneous agents substantially. Also, Kaplan and Violante (2014) show that households with little liquid wealth, i.e. hand-to-mouth households, exhibit a higher MPC than households with a positive amount of liquid wealth.

[35] Aside from Jaspelli and Pistaferri (2014), the evidence on the MPC distribution is scarce partly due to the lack of enough samples to precisely estimate the MPC of subgroups of households. Also, Lewis et al. (2021) show that observable characteristics, such as non-salary income, account at most for a quarter of estimated MPC heterogeneity, implying that MPC may or may not decrease in income or liquid wealth.

Additional results from the main model experiment

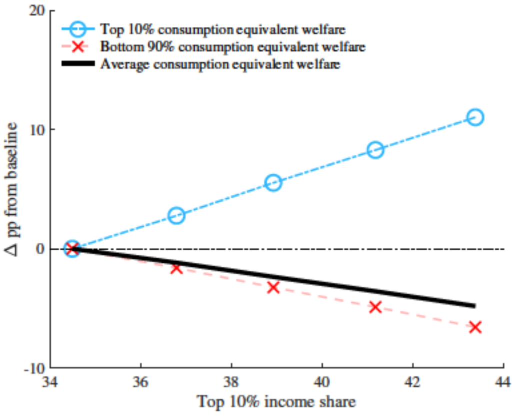
Figure OA11: **GE consequences of rising top income shares - Alternative model**



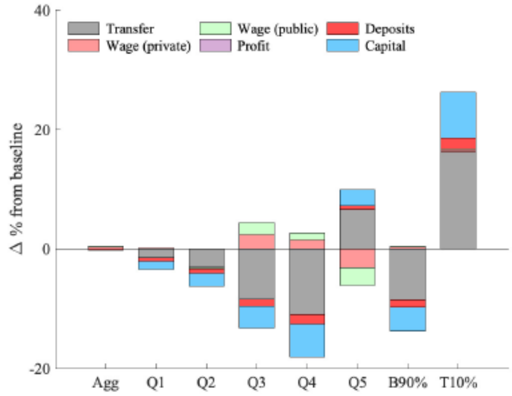
Note: This figure corresponds to Figure 3 in the main text, but shows the same results for the alternative model with fixed portfolio shares.

Figure OA12: **Welfare consequences - Alternative model**

(a) Welfare across households



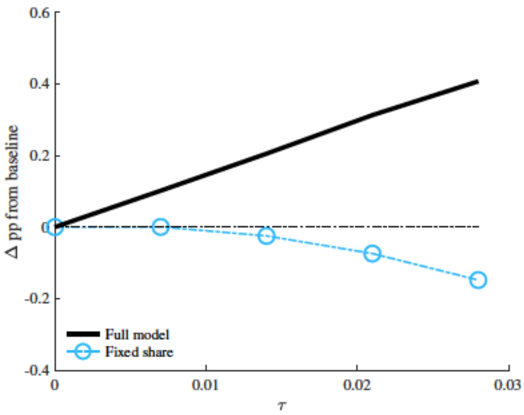
(b) Decomposition of income changes



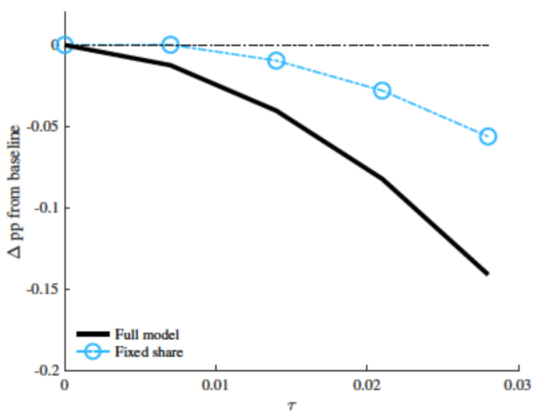
Note: This figure corresponds to Figure 4 in the main text, but shows the same results for the alternative model with fixed portfolio shares

Figure OA13: **GE consequences on prices across model versions**

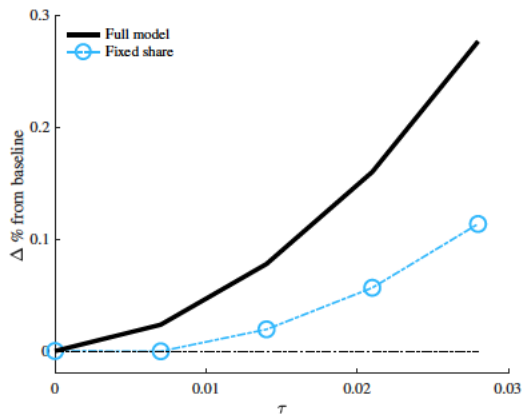
(a) Deposit return



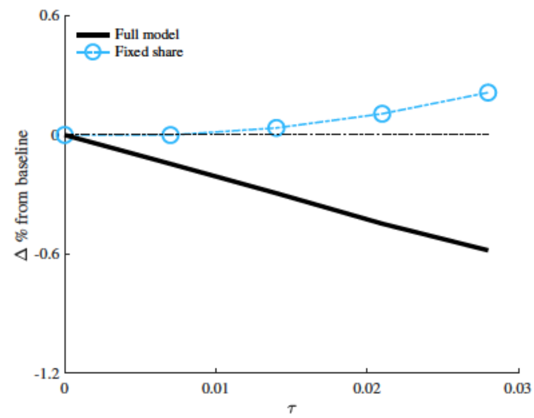
(b) Capital return



(c) Public firm wage



(d) Private firm wage



Note: This figure complements Panel (c) of Figure 5 in the main text, by showing all returns and wages across the two model versions.

Setup of the additional model experiment

Changes in household income processes. We increase the permanent component of the income processes of H-type households in the following way, while keeping L-type households' income processes unchanged:

$$\widetilde{s}_{i,H,t} = s_{i,H,t} + \Delta s_{i,H,t} \tag{60}$$

$$\Delta s_{i,H,t} = \Delta s_H \frac{s^{\varepsilon}_{i,H}}{\hat{s}_H}, \quad \hat{s}_H = \sum_{i=1}^{n_H} s^{\varepsilon}_{i,H} m_{i,H} / \sum_{i=1}^{n_H} m_{i,H}. \tag{61}$$

We set Δs_H to 0.2, which implies about a 40% increase in the H-type aggregate productivity. Among H-type households, those with higher income experience disproportionately larger increase when ε is greater than 1. This flexible setup is similar to how we change lump-sum transfers in our main experiment. We adjust ε to increase the top 10% total income share to about 50% as in our main experiment experiment.

Complementarities between workers and firms. We assume that H-type (L-type) households supply labor only to public (private) firms, a stand-in for (perfect) complementarities between different workers and firms. In this version of the model, households' preferences are altered in the following way:

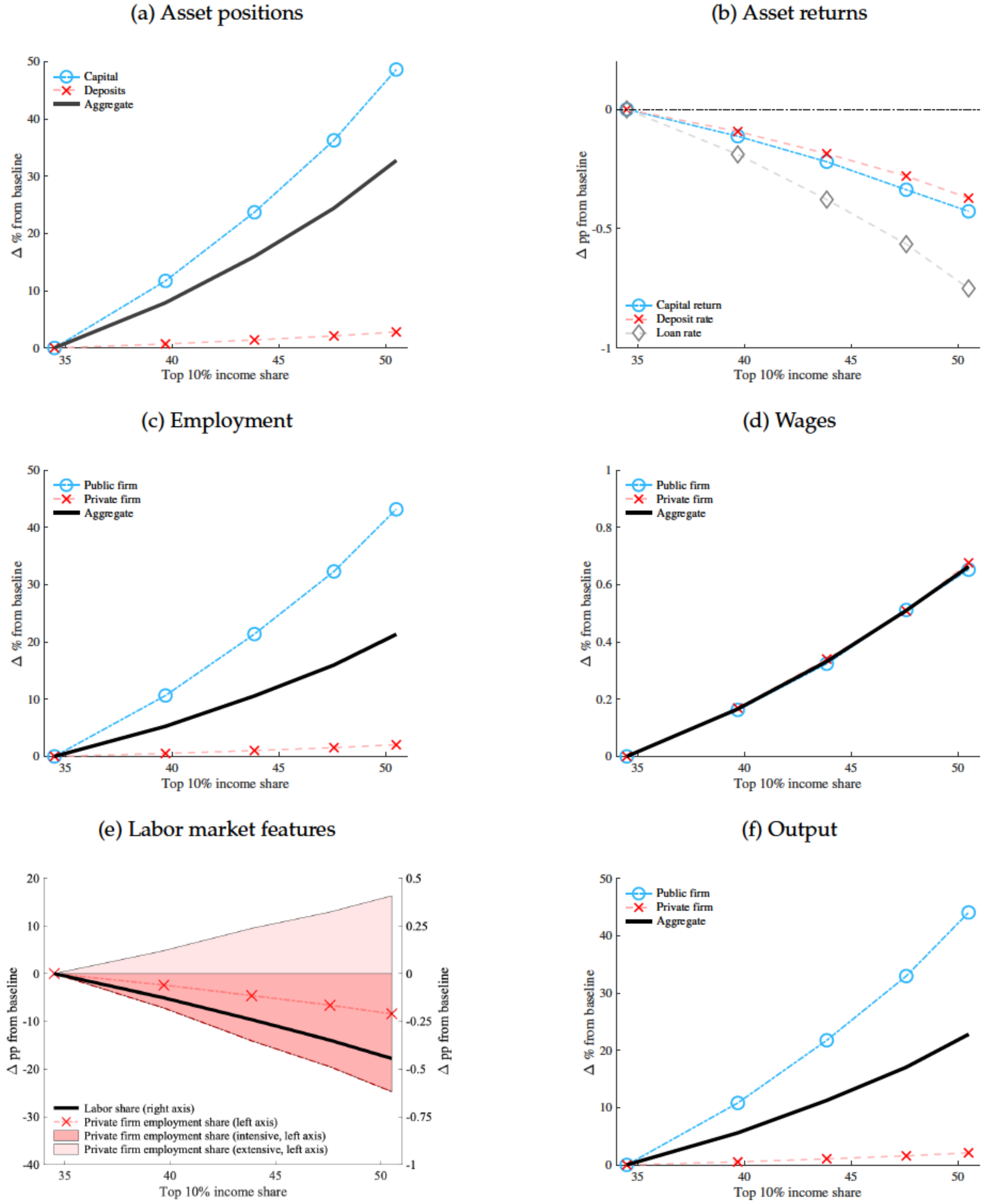
$$\bar{u}(c_{i,\chi}, n_{i,\chi}) = c_{i,\chi} - \psi_\chi \frac{n_{i,\chi}^{1+\frac{1}{n}}}{1+\frac{1}{n}}, \tag{62}$$

for $\chi = H, L$. To ensure that each type of household supplies the amount of labor that demanded by their respective type of firms and to target the public firm employment share, we re-calibrate the disutility parameter ψ_χ. Note that in this setting, the amount of labor supplied by households is different from those in the baseline model. To still set the steady-state wage of each type of labor to 1, without requiring recalibration of other parameters, we also add some lump-sum government transfers/taxes as a normalization.

Further results from the additional model experiment

Figure OA14 complements Figure 6 in the main text, by showing additional model variables.

Figure OA14: **GE consequences of rising top income shares - Alternative experiment**



Note: This figure complements Figure 6 in the main text, by showing additional model variables.