Income Inequality and Job Creation*

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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 costs for bank-dependent firms, which in turn create fewer jobs. Exploiting variation across US states and an instrumental variable strategy, we provide evidence for this channel. To study its aggregate implications, we build a general equilibrium macro model with heterogeneous households and heterogeneous firms. Calibrating the model to our empirical estimates, we show that growing top incomes account for 16% of the decline in the employment share of small firms since 1980, in part through less entry. Rising inequality also reduces the labor share and lowers aggregate output. Our model exercises highlight that ignoring the link between inequality and job creation understates welfare effects of income redistribution.

JEL classification: D22, D31, E44, E60, L25.

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1 Introduction

The rise in top incomes over the last decades has given new impetus to the long-standing debate on how income inequality affects the real economy (Jones, 2015). Recent macroeconomic 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 improve funding conditions for firms with access to bond and equity financing. But they increase 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 of the paper builds a quantitative macroeconomic model with heterogeneous households and heterogeneous firms. We use the model to study the consequences of rising top income shares through our proposed channel for macroeconomic outcomes and welfare. Together, our empirical and theoretical 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 (Autor, Dorn, Katz, Patterson and Van Reenen, 2020; Decker, Haltiwanger, Jarmin and Miranda, 2020).

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 large 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 1.6 p.p. The average increase in the income share of the top 10% from 1980 to 2015 was around 10 p.p., so small firms' net job creation rate would be 1.6 p.p., or almost 50%, higher today if top income shares had remained at their 1980 levels.

Rising top incomes reduce job creation both along the intensive and extensive margin. We find that 20% of the overall decline in the net job creation rate is due to lower firm entry and exit. Focusing on firm entry only, the effect of an increase in the top income share on gross job creation of entrants accounts for almost half its overall negative impact on gross job creation. These large effects reflect the importance of banks as a source of funding for entrants and the crucial role of new firms for overall job creation and business dynamism.

We develop an instrumental variable that 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 to address omitted variable bias and reverse causality. 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, 2022). This IV uses industries' beginning-of-period employment shares in each state, interacted with their nationwide employment evolution.

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. In these saturated specifications, any unobservable factor that could simultaneously drive job creation and top income shares would need to affect more or less bank-dependent firms within the same state and industry differently.

We provide further evidence for the link between income inequality and firms' funding conditions. First, we show that the magnitude of the effect of rising top incomes on job creation is declining in firm size, consistent with the empirical evidence that smaller firms are increasingly 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. It does so both along the intensive and extensive margin.

To investigate the effect of rising top incomes on deposits directly, we use bank balance sheet data from the US call reports. In bank-level regressions, a rise in top income shares in banks' headquarters state has a significant negative effect on the amount of deposits and a positive effect on banks' deposit expense. The relative fall in quantities and increase in prices is consistent with a relative reduction in households' supply of deposits. Moreover, we show that the effects of rising top incomes on deposits and deposit rates are increasing in the income share threshold (10% vs. 1%), reflecting that deposits as a share of financial assets decline with income. We obtain similar results for commercial and industrial loans: higher top income shares reduce loan amounts but increase interest income. We also rule out alternative explanations, such as demand, the collateral channel, and public goods, for the link between top incomes, funding conditions, and job creation.

We also rule out 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) and those are predominately provided by smaller, bank-dependent firms. To preclude this channel, we exclude non-tradable industries from our regressions and find similar effects. Further, directly controlling for the impact of house prices on small and large firms does not affect the results, suggesting that they are not explained by the collateral channel (Chaney, Sraer and Thesmar, 2012; Adelino, Schoar and Severino, 2015). The results are also robust to controlling for state-level spending on education, implying that they do not arise from changes in the provision of public goods (Braggion, Dwarkasing and Ongena, 2021).

The second part of the paper studies how the large distributional effects of rising top incomes across households and firms 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 of this paper.

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 Straub (2019), the deposit share declines with income through non-homothetic savings behavior. On the production side, the model features a 'public' firm as well as heterogeneous 'private' firms. The public firm receives 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. A competitive banking sector offers deposits to households and provides loans to private firms.

We calibrate the model to target the stylized facts and causal 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 a 10 p.p. 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. An increase in top income shares also leads to an even larger increase in top wealth shares, as observed in the data.

Our quantitative experiment raises the top 10% income share from 30% to 50%, matching its evolution from the 1980s to today. The initial share of 30% results from permanent labor productivity 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.[1]

We first examine macroeconomic outcomes, as well as the impact across firms. With more income accruing to top earners, aggregate direct investments in the public firm 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 direct firm investments falls, while the deposit rate increases. Due to banks' zero profit condition the increase in bank funding costs also raises the loan rate, in line with our empirical findings at the bank level. 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 driven both by active private firms demanding less labor, as well as by fewer firms entering production.

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 directly funded firms. This inequality-induced reallocation of resources increases the employment share of large firms by 0.9 p.p. In the US, the employment share of firms with more than 500 employees has increased by 4.9 p.p. since 1980. Rising inequality thus explains around 18% 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 0.4 p.p., corresponding

[1] If we instead increased top income shares for example by changing productivity levels, then the change in productivity itself would have macroeconomic effects through channels other than rising top income shares. To identify the direct effects of rising inequality, we mute such alternative channels in our experiments.

to around 5%–10% of its decline 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 1%.[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 – i.e. that households adjust their portfolio and thereby affect firms' funding conditions, returns, and wages – 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.

The amplification of the welfare effects arises from changes in different sources of income in equilibrium. First, wage income is more important for lower-income households. 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, 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 the public firm. As direct investments into the public firm 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.

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

[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 the public firm, independent of productivity levels.

[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.

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 macroeconomic model to the cross-regional estimates, similar to studies surveyed in Nakamura and Steinsson (2018).

Second, our paper relates to work on the macroeconomic effects of income inequality arising from the inter-temporal decisions of heterogeneous 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. Building on the insight that richer households finance the borrowing of poorer households (Mian, Straub and Sufi, 2020), they argue high large 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. 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 are heterogeneous in their funding sources usually do not incorporate household portfolio decisions, see e.g. Zetlin-Jones and Shourideh (2017) and Crouzet (2018).

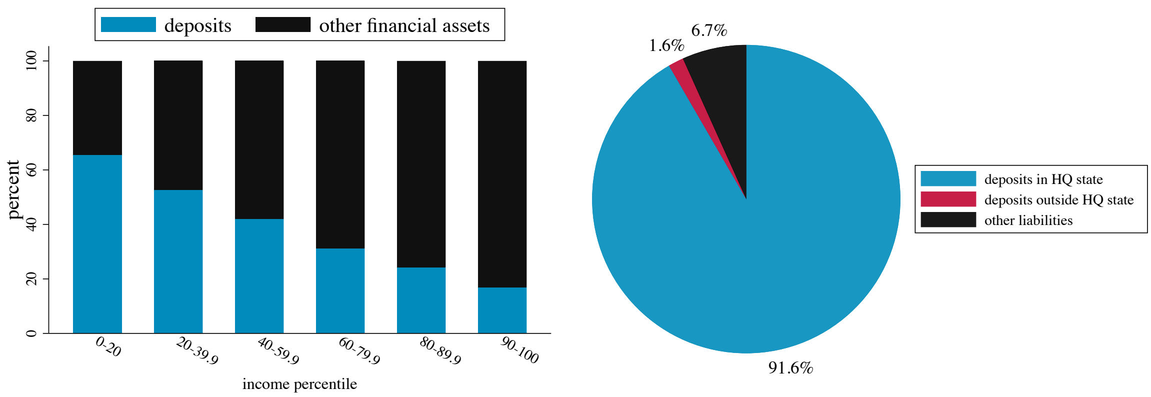
2 Motivating evidence and hypothesis

This section first presents facts on the relation between household income and savings in different financial assets. Second, it examines the relevance of deposits for bank funding, and reviews the literature on the importance of bank lending for firms. Based on these motivating facts, we then develop our main hypothesis.

Figure 1: **Household asset allocation and bank funding sources**

(a) Deposit shares across income groups

(b) Sources of US bank funding



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. Source: SCF. Panel (b) 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. Numbers reflect averages across all banks and years in the sample. Source: FDIC

Household income and asset allocation. We examine the allocation of financial asset across the US household income distribution using data from the Survey of Consumer Finances (SCF) of the Federal Reserve.[4] Figure 1, panel (a) reveals that the share of financial assets held as deposits declines in household income (see also

[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.

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 top 10%. Instead, direct investments such as stocks, bonds, and other financial assets increase with household income (see also Melcangi and Sterk (2020)). 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 on the other hand.

The Online Appendix provides a finer breakdown of asset classes and shows that the deposit share also declines in income within the top 10%. We also verify that the negative relation between income and deposit shares is not explained by a large set of household controls, such as age, education level, occupation, or gender. Furthermore, while panel (a) presents *relative shares* of deposits, 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.

Deposits, bank lending, and bank dependence. The Federal Deposit Insurance Corporation (FDIC) provides information on the sources of funding of all US banks. Figure 1, 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 source of funds in the US banking system suggests that households' supply of deposits has an impact on banks' overall liabilities.

The same panel reveals that the average bank raises around 98% of its total deposits in its headquarters state. 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 (see the Online Appendix for distributional patterns).[5] We exploit the regional dimension of bank funding in our identification strategy, following the idea that the *local* supply of household deposits affects banks' funding conditions.[6]

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

[5] 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%.

[6] Kundu, Park and Vats (2022) show that for both small and large banks, at least 30% of deposits for a given bank are concentrated in a single county.

incurring costs (Stein, 1998).[7]

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).[8] Likewise, banks play an outsized role in financing new firms (Robb and Robinson, 2014; Kerr and Nanda, 2015), suggesting that the availability of bank credit also affects firm entry.

In the Online Appendix we show that, similar to deposits, banks extend the majority of their small business loans in their home state. Aggregate trends from the US Financial Accounts show that deposits as a share of household assets have fallen over the last few decades, while bonds and equities have increased. Similarly, the share of C&I loans in business sector liabilities has decreased, while the share of bonds and equities has risen.

Main hypothesis. Motivated by the 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 share of total financial assets is held in the form of stocks and bonds. Funding costs subsequently decline for firms that make greater use of equity and bond financing, which are generally large firms. Meanwhile, the share of deposits declines, increasing the cost of funds for banks. Since banks have a comparative advantage in screening and monitoring opaque firms, this leads to a relative decline in the availability of financing for bank-dependent firms, which are predominately small firms and new entrants. In turn, they create fewer jobs. The following sections first investigate this hypothesis empirically, and then study the implications for macroeconomic outcomes and household welfare in a quantitative model.

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 variables.

[7] For further research on the importance of bank deposits, see Gatev and Strahan (2006); Heider, Saidi and Schepens (2019); Supera (2022).

[8] See also Beck and Demirguc-Kunt (2006) and Jiménez, Ongena, Peydró and Saurina (2017). 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).

3.1 Data

Job creation. Data from the Business Dynamics Statistics (BDS), provided by the U.S. 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 of the net JCR is that it can be decomposed into an extensive (entry and exit) and intensive (continuing establishments) margin.[9]

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). 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.

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

[9] 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: $net\ JCR = JCR - JDR = JCR\ births + JCR\ continuers - (JDR\ deaths + JDR\ continuers) = (JCR\ births - JDR\ deaths) + (JCR\ continuers - JDR\ continuers) = net\ JCR\ extensive + net\ JCR\ intensive.$

or expand their business (Doerr, 2021). In the average industry one-third of firms obtain bank credit, with a standard deviation of 10%.[10] We split industries into high and low bank dependence along the median.

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 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 OA4).

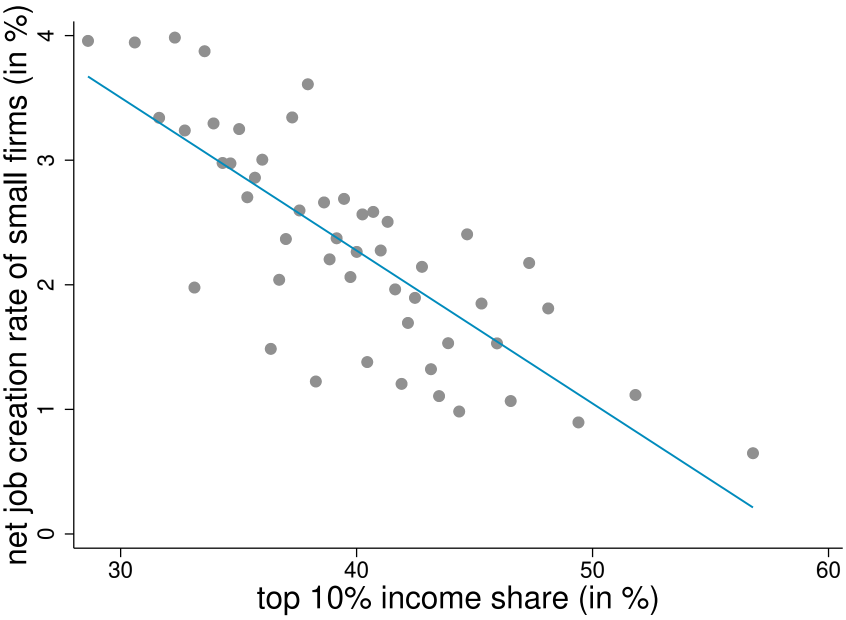
3.2 Empirical strategy

This section empirically tests our channel. Motivated by a large literature on the importance of bank lending for small firms, our baseline analysis investigates the effect of rising top incomes on job creation of small relative to large firms.

Figure 2 previews our key finding. It provides 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). In what follows, we formally test the effect of top incomes on job creation of bank-dependent firms relative to larger firms with access to other sources of financing.

[10] 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).

Figure 2: **Top incomes and job creation**



Note: This figure 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.

3.2.1 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.

3.2.2 Identification and instrumental variables

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.

To address these endogeneity issues and assess the causal effect of rising top income shares on job creation, we employ granular time-varying fixed effects and develop two complementary IVs for the top income share.

Fixed effects. 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. In some specifications, we further control for the marginal effect of the state-level control variables on job creation, by interacting them with the *small firm* dummy. Moreover, in regressions at the state-industry level, we include time-varying fixed effects at the 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.

Instrumental variables. We construct two instrumental variables. Our main instrument combines the pre-determined top income share in each state with the national evolution in top income shares over time. The second instrument 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, 2022). This shift-share instrument uses the industries' beginning-of-period employment shares in each state, interacted with the nationwide employment evolution in these industries. We describe the construction of both IVs in what follows. The Online Appendix presents additional details, as well as several tests in support of their validity and relevance (see Section A.1).

Our main 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). Since this IV relies on the same data as the actual top income shares, we can construct instrumental variables for both the top 10% and top 1% income share for the full sample period and all states.

The pre-determined share IV has a highly significant positive relationship with the actual state-level top 10% (1%) income share.[11] 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 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 (Figure OA2 and Figure OA3).

We report several tests in the Online Appendix to support the validity of our instrument in Table OA2. There, we show the strong positive correlation between the IVs 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

[11] Across specifications, the first stage F-statistic always exceeds 75. Figure OA1, panel (a) provides further details on the relationship.

or 5,000 or more employees from the analysis, as these 'mega firms' experienced a substantial increase in employment and earnings (Haltiwanger, Hyatt and Spletzer, 2022). Our results remain robust across specifications.

Our second instrument (henceforth 'Bartik IV') follows a shift-share research design, based on the insight that income inequality is driven by a small subset of industries. Using linked employer-employee data from the Longitudinal Employer-Household Dynamics (LEHD), Haltiwanger, Hyatt and Spletzer (2022) show that just 30 4-digit NAICS industries ('top-30 industries' henceforth) account for most of the rise in overall earnings inequality since 1990, but only a modest share of aggregate employment.[12] 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 the top-30 industries. And second, heterogeneity in the nation-wide employment trends for these industries: $Bartik\ IV_{s,t} = log\left(\sum_{i \in I} \frac{emp_{s,i}}{emp_s} \times emp_{i,t}\right)$. The BDS provide employment data for each top-30 4-digit industries i over time. To compute initial employment shares (averaged over 1985-1990) we use the County Business Patterns. 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).

The Bartik IV exhibits a strong and highly significant positive relationship with the top 10% income share (Figure OA4). We again verify that the initial employment share of the top-30 industries in a state is uncorrelated with its initial firm size distribution (Figure OA5). It is hence unlikely that firm-specific shocks that vary systematically across states and are correlated with top income shares explain the initial footprint of the top-30 industries. Recent papers discuss threats to the validity of shift-share instruments (Adao, Kolesár and Morales, 2019; Goldsmith-Pinkham, Sorkin and Swift, 2020; Borusyak, Hull and Jaravel, 2022).[13] One threat is that the employment share of a given 4-digit industry within states is high, so that the Bartik IV mostly captures exposure to one industry. However, for the initial employment share of top-30 industry i in state s out of total employment in state s, the mean (median) employment share is 1.1% (0.6%), with the 95^{th} and 99^{th} percentile equal to 4% and 7.2% (see Table OA1). Another concern is that the employment dynamics of a given industry within one state drive aggregate employment dynamics in the industry. The mean (median) initial employment share of industry i in state s is just

[12] 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.

[13] As the shares of the top-30 industries do not add up to one in a state, we verify that controlling for the 'incomplete shares' (Borusyak et al., 2022) does not affect our results.

2% (1%) of total employment in industry i, with the 95^{th} and 99^{th} percentile equal to 6.7% and 14.8%. The fact that the vast majority of top-30 industries accounts only for a small share of total industry- or state-level employment dispels concerns that our Bartik IV is mostly capturing variation in just one or two industries. Table OA3 reports results from similar tests as for the pre-determined share IV in support of the validity of the Bartik IV.[14]

The Bartik IV has two drawbacks relative to the pre-determined share IV. First, the analysis in Haltiwanger, Hyatt and Spletzer (2022) uses LEHD data from 1990 onward, so constructing the Bartik IV for the full sample period requires the assumption that the same 30 industries drive inequality before 1990. Second, the Bartik IV does not allow us to construct separate instruments for the top 10% and top 1% income share that we use in our bank-level analysis. We therefore use the IV based on pre-determined top income shares as our main IV.

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 results for equation (1) using our main IV based on pre-determined shares.[15] 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. A 10 p.p. increase in the share of income that accrues to the top 10% income earners leads to a decline in the relative net job creation rate of small firms by 1.24 p.p.

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).

[14] In addition, we show that our IV results hold in regressions with state*industry*size fixed effects. With these fixed effects, we only exploit variation in how inequality affects the relative job creation of small firms *within* industries. This specification addresses the concern that states with rising top income shares see a shift in job creation towards larger firms in industries that are responsible for the rise on top income shares and could be part of the Bartik weights.

[15] We provide results from OLS regressions and from regressions with the Bartik IV in the Online Appendix. See Table OA11 and Table OA12.

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 pre-determined 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.

To put our estimates into perspective, the average increase in the state-level income share of the top 10% from 1980 to 2010 was around 10 p.p. Hence, relative net job creation of small firms would have been 1.2–1.6 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 of 1.61 p.p. in small firms' net job creation rate for a 10 p.p. increase in the top 10% income share, around 20% are due to a reduction of net job creation along the entry-exit margin.

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 10 p.p. rise in the top income share has a significant negative effect of 4.02 p.p. on the gross job creation rate of small firms (24% of the mean).[16] The inequality-induced decline in job creation of entrants accounts for 47% (1.89 p.p.) 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 large effects of rising top incomes shares on gross job creation through entry reflect the importance of banks as a source of funding for startups (Robb and Robinson, 2014; Kerr and Nanda, 2015), as well as entrants' importance for overall job creation.

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 21% higher, out of which almost half (or 10%) 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 0.27 p.p. decline induced by the 10 p.p. increase in the top 10% between 1980 and 2010 hence reflects a 17% drop in the net job creation rate through lower entry and exit.

4.2 Further evidence on the mechanism

In what follows we provide additional evidence consistent with the hypothesis that rising top incomes affect job creation through their effect on bank deposits and thereby firms' financing conditions.

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

[16] We also show that the reallocation rate declines by relatively more among small firms as top income shares increase.

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 contraction in credit should hurt firms in this industry by more than those in other industries. We estimate regressions analogous to regression (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 hypothesis asserts that an increase in top income shares has a negative effect on households' supply of bank deposits. As deposits represent the cheapest and most-stable source of funding for banks, a negative shift in their supply increases the cost of funds for banks, and thus increases the cost of credit for firms. An increase in the top income share in a state should thus have a negative effect on the amount of bank deposits, and a positive effect on interest rates on 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 log amount of total deposits or the ratio of deposit expenses to total deposits of bank b headquartered in state s in year t.[17] The

[17] The ratio of deposit expenses to deposits proxies deposit rates. It reflects the average expense on existing and new deposits and is hence less responsive to changes in the deposit supply than the actual deposit rate offered to new customers.

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 highly skewed distribution in bank size, we weight regressions by banks' 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 reduce bank deposits, 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 1, 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 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.

Table 2 shows that rising top incomes lead to a relative decline in deposits and an increase in the deposit rate. Columns (1)–(2) use the log of total deposits as dependent variable. Column (1) shows that a 10 p.p. increase in the instrumented top income share leads to a 24% 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 10 p.p. between 1980 and 2010. Over the same period, aggregate deposits as a share of household non-financial assets have declined by around 50% (see Figure OA9 in the Online Appendix).

As discussed in Section 2, a given increase in the top 10% income share should affect banks' ability to finance firms 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 OA6 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.[18]

Columns (3)–(4) use the deposit rate as dependent variable and show that the

[18] We confirm in the Online Appendix that a similar increase in top income shares also leads to an stronger negative effect on job creation of small firms for the 1% income threshold, compared to the top 10% threshold.

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

VARIABLES	(1) log(dep)	(2) log(dep)	(3) dep rate	(4) dep rate	(5) log(CI)	(6) CI rate
top 10% income share	-2.436***		2.639***		-2.364***	12.283***
	(0.588)		(0.653)		(0.638)	(4.651)
top 1% income share		-4.928***		2.942***		
		(1.134)		(1.077)		
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 log amount of total bank deposits in columns (1)–(2) and the ratio of deposit expenses to total deposits in columns (3)–(4). In columns (5)–(6), the dependent variable is the log amount of total bank C&I lending and the ratio of C&I interest income to total 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.

price of deposits increases significantly as top income shares rise. In column (3), a 10 p.p. increase in the predicted top income share increases the deposit rate by 0.26 p.p. (28% of the mean and 0.51 standard deviations). Column (4) again shows that rates increase by more the higher the income threshold. These results thus suggest that a rise in top income shares leads to a relative decline in the *quantity* of deposits, but increases their *price*. This pattern is consistent with a relative decline in the supply of local deposits by households as state-level top income shares rise.

Bank loans and loan rates. Finally, columns (5)–(6) of Table 2 show that higher top incomes also reduce banks' C&I lending and increase their interest income on C&I loans. This pattern suggests that rising top incomes, through their effect on the supply of bank deposits, affect banks' credit supply to firms, thereby hurting bank-dependent businesses more than those that can access financing without banks. 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.[19]

[19] 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).

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 OA7). First, we ensure that the relationship is not explained by a collateral or wealth channel (Hurst and Lusardi, 2004; Chaney et al., 2012; Adelino et al., 2015) by controlling for house price growth or excluding states with a housing boom. 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 our results, which ensures that our channel is distinct from Braggion, Dwarkasing and Ongena (2021). Further, we move to state-industry-firm size-year level regressions and exclude non-tradable industries. 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. Finally, we 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 additional robustness tests we exclude the years of the Great Recession, years of economic downturns, the post-crisis period, as well as years with housing booms.

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 of different sizes. We calibrate the parameters to match our empirical estimates. Section 6 presents quantitative experiments using the model.

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, a representative 'public' firm, a continuum of 'private' firms, and a representative bank. We describe these different types of agents in turn.

Households. There is a unit mass of households indexed by i. Households differ in their idiosyncratic labor productivity $s_{i,t}$. Each household supplies labor to both the public firm and private firms, taking respective wages w_t and $\widetilde{w}_t$ as given.[20] Households decide how much to consume, how much to save, and how to allocate their savings. Specifically, households can make deposits $d_{i,t}$ at a bank or invest directly in the capital $k_{i,t}$ of the public firm. These two assets differ in their returns $R_{d,t}$ and $R_{k,t}$. Our calibration will imply $R_{d,t} < R_{k,t}$.

Deposits and direct firm investments differ in the services they provide. We assume that bank deposits give utility, which generates in a tractable way the empirical fact that the share of deposits in savings decreases in income, while the amount of deposits increases in income. We introduce a utility specification that borrows insights from Straub (2019). 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, $n_{i,t}$ and $\widetilde{n}_{i,t}$ are labor supplied to public and private firms. We assume $\eta > \sigma$, which generates non-homotheticity in preferences, making deposits a *necessity good*. Households with a low level of income and wealth hold a larger share of deposit in their portfolio than those with a high level. Straub (2019) makes a similar assumption to generate an increasing share of overall savings by making wealth (bequests) a *luxury good*.[21] Our assumption is a stand-in for unmodeled structural factors that change the deposit share along the income distribution. One example are liquidity services that benefit households at different income levels to a different degree, e.g. because of health risk.[22] The Online Appendix provides evidence from the SCF that households' self-reported savings for "emergencies and other things that may come up", scaled by income, fall with income.

[20] By having each household supply labor to both types of firms, we abstract from any effects of sorting in the labor market. We discuss this possibility further below.

[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 pension 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.

The household's objective is to maximize expected lifetime utility

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

subject to

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

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

where $\Pi_{i,t}$ are profit rebates from firms and $T_{i,t}$ is a lump-sum transfer or tax. In our quantitative experiments 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.

Public firm. A representative public firm of mass 1 produces consumption good Y_t, using capital K_t and labor N_t, according to the production function

$$Y_t = ZK_t^{\theta}N_t^{\gamma-\theta}, \tag{7}$$

where Z is total factor productivity (TFP), $0<\theta<1$ is the share of capital, and $0<\gamma\leq 1$ governs the returns to scale in production. Profit maximization implies

$$R_{k,t} = \theta Z\big(K_t\big)^{\theta-1}\big(N_t\big)^{\gamma-\theta}+1-\delta, \tag{8}$$

$$w_t = (\gamma-\theta)Z\big(K_t\big)^{\theta}\big(N_t\big)^{\gamma-\theta-1}. \tag{9}$$

The depreciation rate of capital is denoted by δ. 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.

Private firms. The economy is populated by a continuum of mass $\widetilde{\mu}$ of private firms, indexed by j. Private firms produce consumption goods $\widetilde{y}_{j,t}$ according to

$$\widetilde{y}_{j,t}=\widetilde{z}_j\widetilde{n}_{j,t}^{\alpha}-\widetilde{f},\ \alpha<1, \tag{10}$$

where $\widetilde{n}_j$ is firm j's employment. Idiosyncratic productivity $\widetilde{z}_j$ is distributed uniformly on the interval $[\widetilde{z}_{min},\widetilde{z}_{max}]$. $\widetilde{f}$ is a fixed cost. The assumption of decreasing returns ($\alpha<1$) pins down a firm's size. The fixed cost gives rise to a cutoff productivity $\underline{\widetilde{z}}$ above which firms decide to enter and produce. This allows us to study effects of inequality on private firm employment along the intensive and extensive margin, as in our empirical analysis.

Private firms do not have access to public capital markets, but instead require bank funding. Specifically, they finance their fixed cost as well as a share ϕ of their wage bill at the beginning of period t with a bank loan at gross interest rate $R_{\ell,t}$. Private firms maximize their profit

$$\widetilde{\pi}_{j,t} = \widetilde{z}_j \widetilde{n}_{j,t}^{\alpha} - \widetilde{f} - \widetilde{w}_t \widetilde{n}_{j,t} - (R_{\ell,t} - 1)\left[\widetilde{f} + \phi \widetilde{w}_t \widetilde{n}_{j,t}\right]. \tag{11}$$

In this setting, the cutoff productivity level $\underline{\widetilde{z}}$ is pinned down by

$$\widetilde{\pi}_{j,t}[\widetilde{n}_{j,t}^{*}(\underline{\widetilde{z}})] = 0, \tag{12}$$

where $\widetilde{n}^{*}(\widetilde{z}_j)$ is the optimal employment choice conditional on operating, with

$$\widetilde{n}^{*}(\widetilde{z}_j) = \left[\frac{\alpha \widetilde{z}_j}{\{1 + (R_{\ell,t} - 1)\phi\}\widetilde{w}_t}\right]^{\frac{1}{1-\alpha}}. \tag{13}$$

We use conditions (12) and (13) to illustrate private firms' behavior with comparative statics: for a given wage, $\frac{\partial n_{j,t}^{*}}{\partial R_{\ell,t}} < 0$, $\frac{\partial \underline{\widetilde{z}}}{\partial R_{\ell,t}} > 0$, $\frac{\partial^2 n_{j,t}^{*}}{\partial R_{\ell,t}\, \partial \phi} < 0$, and $\frac{\partial^2 \underline{\widetilde{z}}}{\partial R_{\ell,t}\, \partial \phi} > 0$. These derivatives reveal how the model incorporates the findings of our empirical analysis. In general equilibrium, the effect of higher top income shares will operate through lower aggregate deposit supply pushing up the loan rate. 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 enter production. The strength of these 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.

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. Thus, the zero profit condition for the bank and the loan market clearing condition imply:

$$R_{\ell,t} = R_{d,t} + \frac{\Xi}{D_{t+1}}, \tag{14}$$

where D_t is the total amount of deposits in the economy.[23]

[23]The fixed cost in the banking sector makes the loan rate respond more than the deposit rate to changes in deposit supply, and thus to changes in top income shares, as in our empirical analysis.

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, solving it is facilitated by the fact that we abstract from aggregate risk, and that the firm problems are static. Making these modeling choices allows us to use an algorithm that 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 US economy as a whole 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 from 30% to 50%, capturing 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 productivity $s_{i,t}$. There are permanent ex-ante differences between two types of households $\chi = L, H$, with mean productivity 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 $\bar{u}(c_i, n_i, \widetilde{n}_i) = c_i - \psi_n \frac{n_i^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}} - \widetilde{\psi}_n \frac{\widetilde{n}_i^{1+\frac{1}{\nu}}}{1+\frac{1}{\nu}}$. Note that in our setting, both household types work at both firm types, but the model could be generalized to reflect sorting between households and 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 if anything 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.[24]

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 0.92, implying a quarterly autocorrelation of 0.98. The standard deviation is set to 0.12, based on Storesletten, Telmer and Yaron (2004).[25] The mass of each household type captures the actual size of the top 10% and bottom 90% income groups. The degree of decreasing returns to scale in both production functions is set to 0.9.

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 the public and private firm labor that households desire to 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 two parameters to match the deposit share of the middle quintile and the top 10% income in the SCF in the early 1980's (0.45 and 0.22). β governs households' overall desire to save, and is calibrated to match the net return on public firm capital to the historical average of US stock returns of around 8%. In the income processes

[24]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.

[25]We discretize each income process with 7 grid points.

s_L is normalized to 1, while s_H is calibrated to ensure that the initial top 10% income share equals 30%, 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 1980's**

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	α	Private firm returns to scale	0.9
σ_ϵ	Standard dev. of productivity process	0.12	γ	Public firm returns to scale	0.9

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)	0.0642	0.45	0.45
η	Elasticity of deposit utility	Top 10% deposit share (SCF)	3.14	0.22	0.22
β	Household discount factor	Mean return US stock market	0.9184	1.08	1.08
s_H	Productivity scale H vs. L	Top 10% income share	3.6828	0.30	0.30
Z	Public firm TFP	Labor demand share 500+ (BDS)	1.1651	0.469	0.469
θ	Public firm capital share	Capital depreciation rate (NIPA)	0.16	0.06	0.06
$\widetilde{z}_{min}$	Lower bound private firm TFP	Employment smallest private firm	0.6386	1	1
$\widetilde{z}_{max}$	Upper bound private firm TFP	Employment largest private firm	1.1905	500	500
$\widetilde{\mu}$	Mass private firm sector	Labor supply share 1-499 (BDS)	36.8	0.531	0.531
ϕ	Private firm bank dependence	Int. margin estimate: Table 1 Col (3)	0.981	-0.133	-0.133
$\widetilde{f}$	Private firm fixed cost	Ext. margin estimate: Table 1 Col (4)	0.0021	-0.027	-0.027
Ξ	Banking sector fixed cost	Mean of US deposit rates	0.2173	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 the public and private firms also correspond to the targeted sectoral employment shares. We set TFP of the public firm Z such that it demands 46.9% of total labor. Given the level of public firm employment that results from this choice, we calibrate the bounds of the private firm productivity distribution so that the implied employment levels across firms correspond to the relevant size buckets in the BDS. Specifically, the average firm with more than 500 employees in the BDS has 2,750 employees, so we set $\widetilde{z}_{min}$ and $\widetilde{z}_{max}$ such that $N/\widetilde{n}(\widetilde{z}_{max}) = 2750/500$ and $N/\widetilde{n}(\widetilde{z}_{min}) = 2750/1$. The mass of private firms $\widetilde{\mu}$ is then adjusted so that total private firm labor demand corresponds to 53.1% of total labor demand. The parameter in the working capital constraint ϕ and the fixed cost $\widetilde{f}$ are set to precisely reproduce our empirical estimates in Table 1, for the extensive and intensive margin. Banks' fixed costs imply a deposit rate of 4%, consistent with US data on average over the period we consider.

Specification of the experiment. We increase the top 10% share from 30% to 50%, matching its evolution from the 1980s to today (Saez, 2018). We generate this increase through permanent lump-sum transfers between households, to remain agnostic about the multi-faceted sources of the rise in top income shares, and to abstract from any *direct* relation between macroeconomic trends and top incomes. Such a relation would be present, for example, if we changed top incomes by moving productivity differentials between households or firms. Instead, our exercise studies the effects that arise exclusively through portfolio re-allocation.[26]

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 $\varphi = 3$. τ is equal to 0.038.[27]

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). The model does not target MPC and MPS but 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. While our calibration does not directly target these facts, they are consistent with the data and thus provide additional validation of the model.

[26]The model is general enough to alter income inequality in other ways, for example through specific drivers of inequality suggested in the literature (Cowell and Van Kerm, 2015). It could also be used to study the macroeconomic consequences of specific aspects of tax systems, such as progressivity. See e.g. Heathcote, Storesletten and Violante (2017) for a recent study.

[27]As the transfer amount (tax) is based on households' productivity, it affects their income *level* as well as the idiosyncratic income *risk*. Thus, depending on the relative magnitudes of income level and risk effects, the aggregate household response to the transfer can vary. We design the transfer scheme to ensure the consistency between model responses and our empirical results.

6 Quantitative experiments in general equilibrium

Our empirical results suggest that rising top incomes have large distributional effects across households and firms. To examine the macroeconomic consequences, our general equilibrium model experiment raises the top 10% income share permanently from 30% to 50%. We also characterize implications for welfare.

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 30%. Panel (a) shows that, as deposits are more important for low-income households than for 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 almost 4%, savings flow to a larger extent into the public firm's capital, leading to an increase of roughly 2%. These patterns are a consequence of the non-homotheticity in preferences over different assets. Relatively more income accruing to high-income households also slightly raises aggregate savings.[28] This shows that total savings rates in the model can increase in permanent income, as in Dynan, Skinner and Zeldes (2004) and Straub (2019).[29]

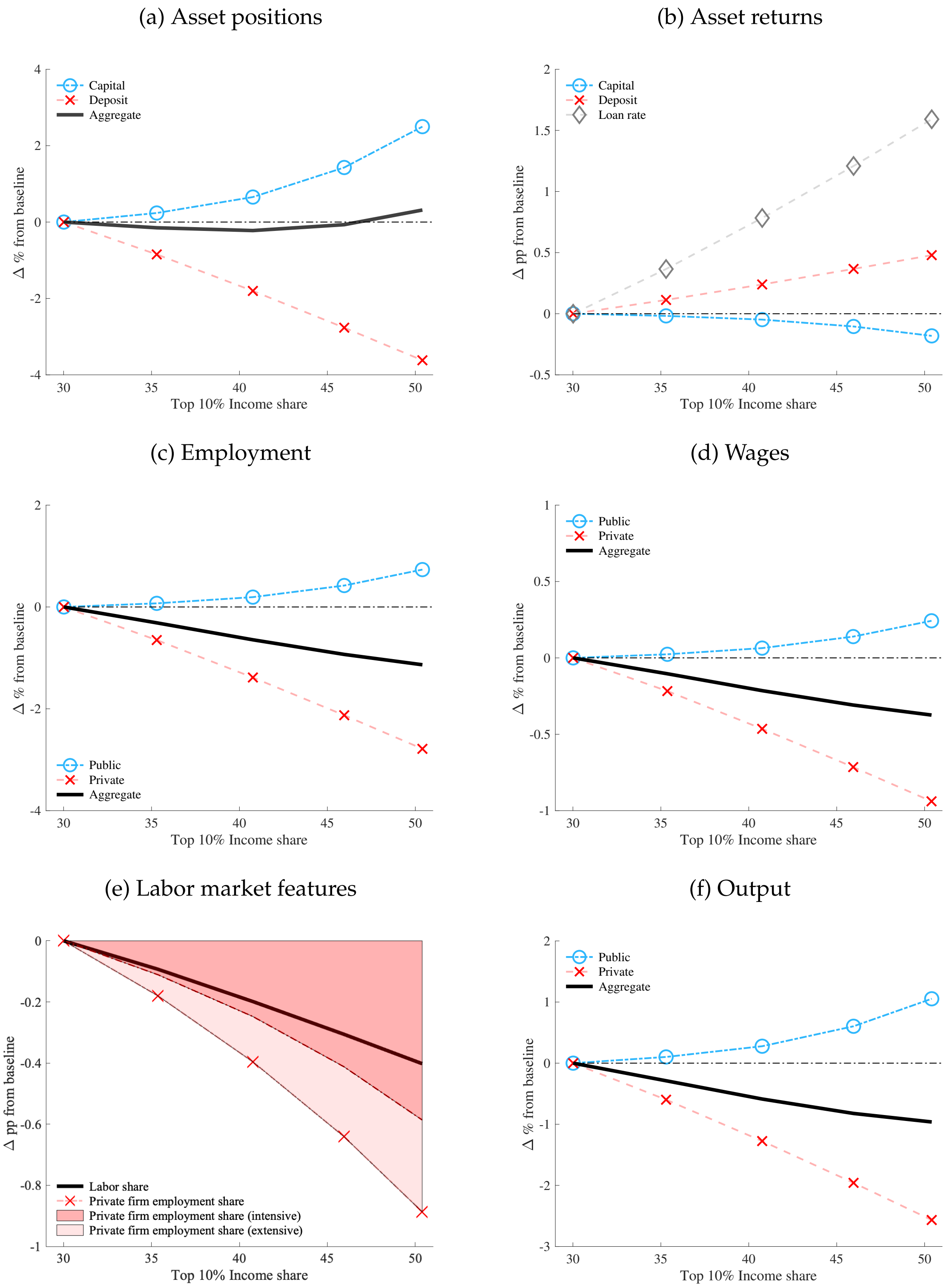
Panel (b) shows how a higher top income share affects the returns on different assets. The return on direct firm investments, determined by the public firm's marginal product of capital, falls by about 0.2 p.p. The deposit rate increases by 0.5 p.p., raising loan rates by roughly 1.5 p.p. due to banks' 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 capital falls. We show in addition that returns on different assets are moved 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.[30]

[28] Aggregate savings only slightly increase in the exercise because our empirical results are consistent with only small changes in aggregate savings in response an increase in top income shares. If overall savings significantly increased due to rising income inequality, it would lead to only a relative decrease in deposits compared to direct investments but an absolute increase, leading both the deposit and loan rate to fall. Such a pattern would be inconsistent with our estimates.

[29] While in partial equilibrium savings increase substantially, the relationship between top income shares and total savings is nonmononotic in general equilibrium, with a reduction in savings until the top income share reaches 45%.

[30] See Xavier (2021) for an analysis of return heterogeneity in the SCF.

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



Note: Selected equilibrium quantities and prices for different top 10% income shares. 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 30%.

Our private firm comparative statics above make clear that the higher loan rate puts downward pressure on private firm labor demand, and will make it more costly for private firms to enter production. Panel (c) confirms that the rise in the top income share implies almost 3% lower equilibrium employment in the private firm sector. Conversely, the public firm sector, which now receives more capital, increases employment by a bit less than 1%. We discuss the decline in aggregate employment below, when we interpret the behavior of aggregate output.

Panel (d) shows that wages increase at the public firm 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 models' labor markets. On average, wages in the economy fall.

Panel (e) shows that the share of total employment in private firms decreases by 0.9 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 4.9 p.p. Rising top incomes, through their effect on funding conditions, can thus explain sizeable 18% 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, firms on a smaller interval of productivity decide to produce 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 also falls by 0.4 p.p. as top income shares rise, 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 macroeconomic 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 between 2 p.p. and 4 p.p., so our channel explains 5% to 10% 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 1%, 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. On the other hand, higher top income shares reallocate 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-third higher than that of the public firm. 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.[31] This difference in *marginal* products can be present even when the *level* of TFP of larger firms is higher than that of smaller firms, as some research suggests (Autor, Dorn, Katz, Patterson and Van Reenen, 2020). Indeed, our calibration in Table 3 shows that Z is larger than most of the interval $[\widetilde{z}_{min}, \widetilde{z}_{max}]$, and exceeds the entry cutoff $\widetilde{\underline{z}}$ implied by the calibration.

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, wages, and firms. Our experiment suggests that a sizeable fraction of the increase in the employment share of large firm as well as 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 effects across households, with significant implications for welfare.

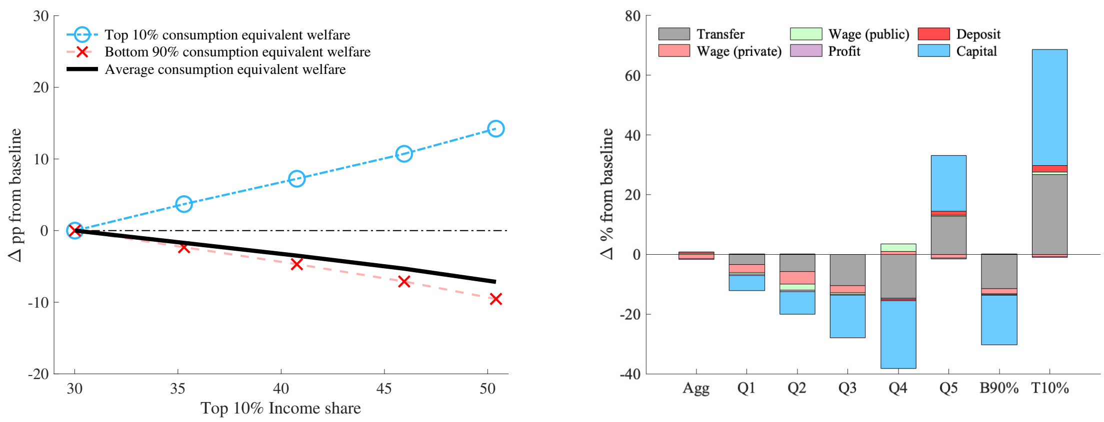
6.2 The welfare effects of rising top income shares

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 groups into different sources. Capital income increases at the top and decreases at the bottom. Wage income declines by most among households in the bottom 40% of the income distribution.

[31] To be precise, our calibration incorporates the differential responsiveness in job creation across firms as follows. In the initial equilibrium, both wages are normalized to 1. The public firm's marginal product is equal to the wage, while the private firm marginal product is higher than the wage because of the financial friction. The magnitude of the difference is governed by ϕ and $\widetilde{f}$, which are chosen to exactly match the estimates in Table 1.

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

(a) Welfare across income groups (b) Decomposition of income changes



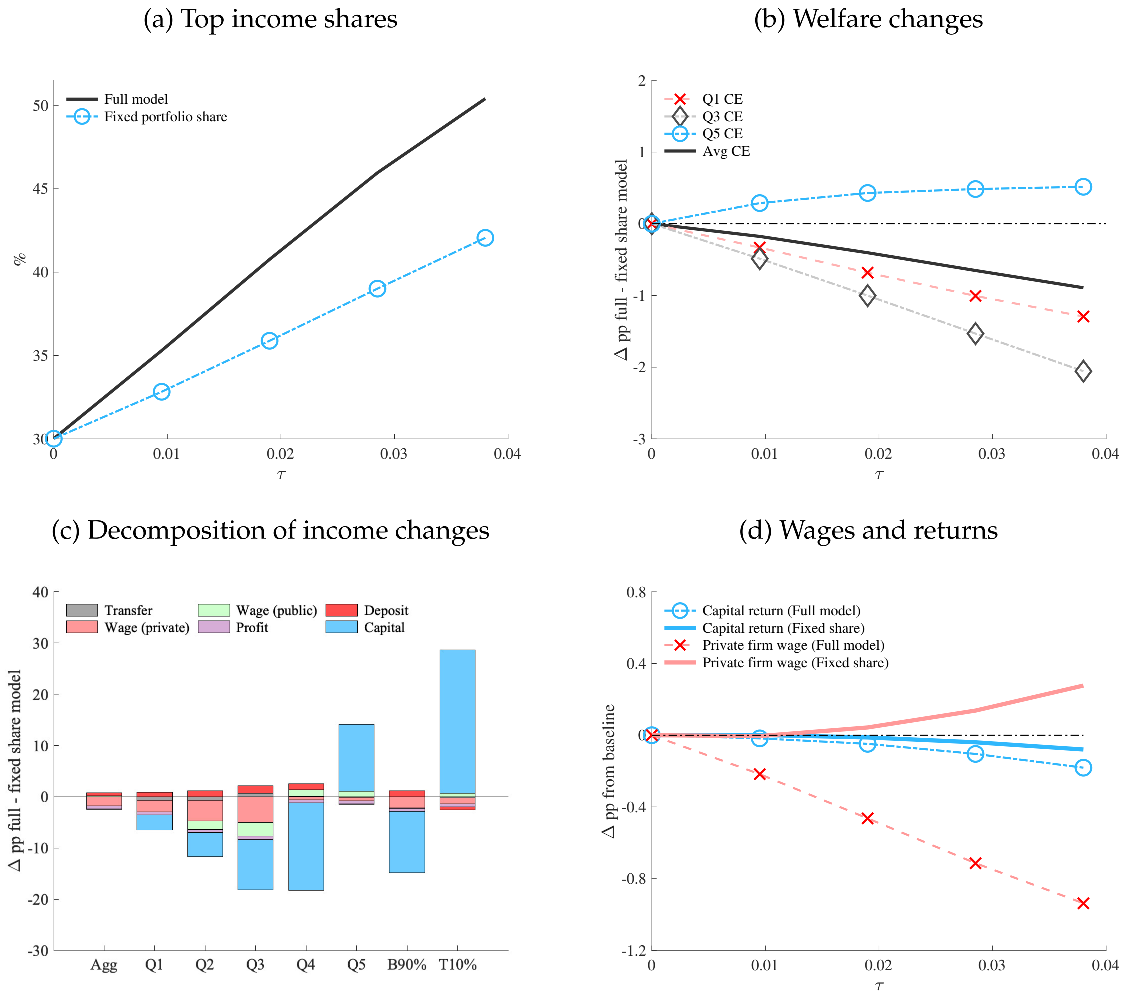
Note: Welfare effects (in consumption equivalents) for different top 10% income shares and decomposition of income changes between the highest at the lowest top 10% income share for different income groups. The calibration shown in Table 3 is used for the initial stationary equilibrium with a top 10% income share of 30%.

Welfare in a model with fixed portfolio shares. By construction, our redistribution of income benefits 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 the public firm. 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 discuss in comparison to the full model.

Contribution of the portfolio allocation channel to welfare effects. 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 at the end of Section 5). Recall that our experiment is designed to generate a change in the top 10% income share from 30% to 50% 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, then the top 10% income share rises only up to around 40% in equilibrium. Our mechanism thus amplifies the effects of the initial redistribution on the rise in the top income share.

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 30%.

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 compare the average household as well as the top, middle and bottom quintiles, where Q5 represents the top 20% earners. 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. In other words, 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 our full model and the fixed portfolio share model across income groups and decomposes it into different sources.[32] By benchmarking the experiment against an alternative model, the direct effect of exogenous transfers nets out across models. The figure shows that the stronger positive (negative) welfare impact at the top (bottom) in the full model relative to the fixed portfolio share model is driven by differences in both asset and labor income. We focus our discussion on the two components with the largest contribution across income groups, namely income from holding capital in the public firm and wage income from private firms. To inform our discussion, panel (d) plots changes in 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 increase in the 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 in general 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 the public firm rise, average wages across all firms fall.

The full model also implies that capital income rises more strongly for top earners. When receiving the transfer, they shift into the higher-return direct 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. As labor income represents the lion's share of income among households at the bottom of the distribution, the loss in capital income matters less for their welfare. 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.

[32] 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.

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.

Potential additional feedback effects. As a final remark, we note that our experiment abstracts from systematic sorting between workers and firms. Sorting might further enhance the welfare effects of our mechanism, by generating a feedback loop through the labor market. In the current setup, low-income households are impacted by a decrease in *average* wages in equilibrium. If low-income households worked mostly at private firms, and high-income households mostly at public firms, then given the stronger change in private firm wages, low-income households' equilibrium wages would fall even more after the initial change in the income. In turn, their savings behavior would imply an additional reduction in deposits, which would decrease private firm wages further, and so forth.

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 in particular by smaller firms and entrants, relative to other firms. Quantitative experiments in a general equilibrium model 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 model further shows that the mechanism 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 more detail and additional tests for our instrumental variables in Section A.1. It then reports further figures and tables to support the stylized facts and empirical analysis in Section A.2. Finally, it provides additional results from the quantitative analysis in Section A.3.

A.1 Instrumental variable strategy

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 specific to large firm increase their relative job creation, and at the same time 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 wages. Omitted variable bias could arise if unobservable state-level factors could be correlated with top income shares and affect firms' job creation.[33]

To address these endogeneity issues and assess the causal effect of rising top income shares on job creation, 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, 2022), 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 auxiliary 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:

$$\widehat{top\ 10\%\ share}_{s,t} = top\ 10\%\ share_{s,1970} \times \frac{1}{S}\sum_{j\neq s}^{S} top\ 10\%\ share_{j,t}. \tag{15}$$

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

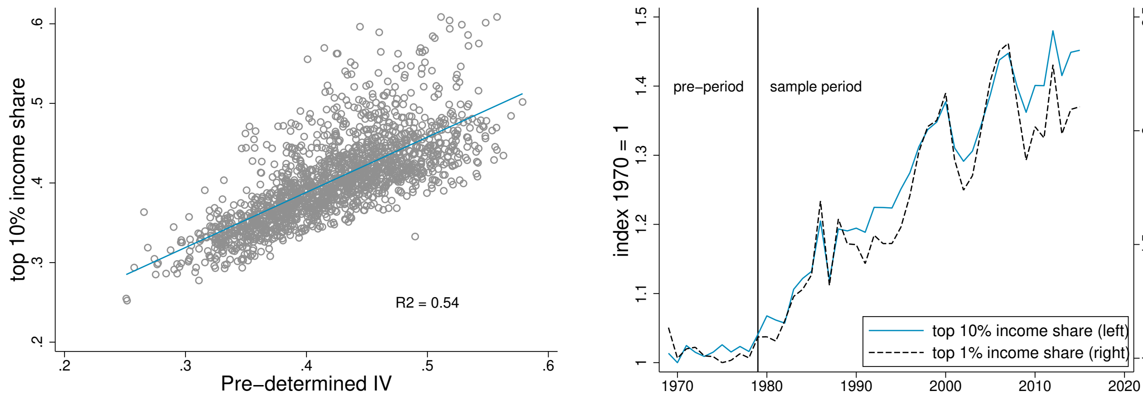
[33]Our inclusion of granular time-varying fixed effects at the state or state*industry level control for any (unobservable) shocks at the state or state-industry level common to firms of different sizes. Yet these shocks could affect small and large firms differentially even within a state or state-industry cell.

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.

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

(a) First stage correlation (b) 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.

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 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.

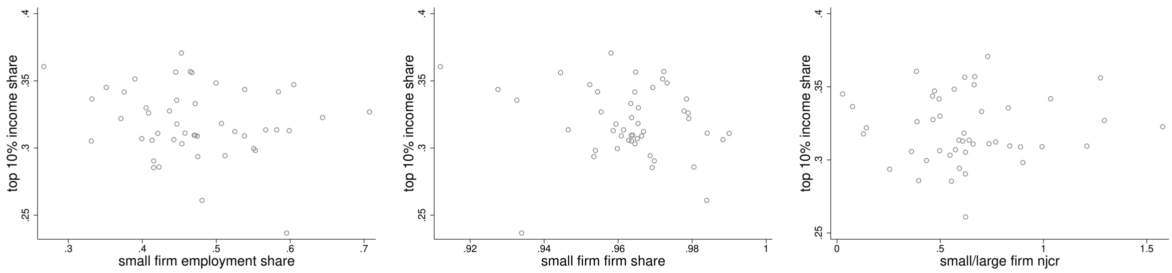
Second, there is no systematic correlation between a state's 1970 top 10% income share and its initial firm size distribution; nor between the initial firm size distribution and its evolution over time. Suppose that states with initially more large firms also had higher income inequality in 1970 because 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.[34] 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).

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.

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.

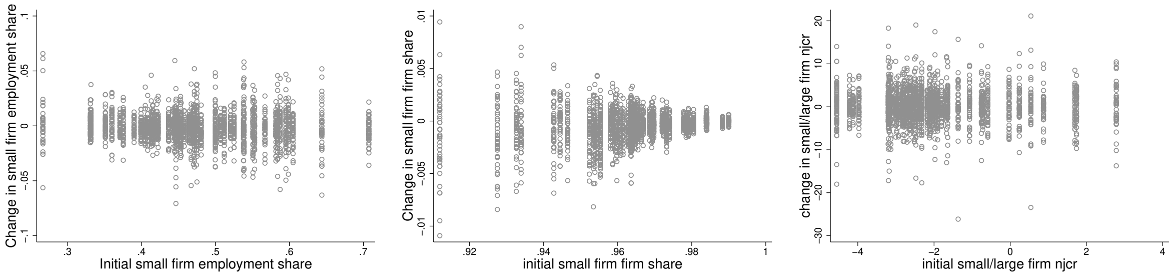
As we will explain in more detail below, we perform additional tests to probe the validity of our instrument. To this end, we exclude the largest firms (i.e. those most affected by technological change) from the analysis; include state*industry*time fixed effects to control for unobservable trends affecting 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. Recent work by Haltiwanger, Hyatt and Spletzer (2022) shows that just 30 4-digit NAICS industries account for most of the rise in overall earnings inequality since 1990. Using detailed

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

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.

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.[35] 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 (2022) ('top-30 industries' henceforth). And second, heterogeneity in the nation-wide employment trends for these industries over time:

$$Bartik\ IV_{s,t} = log\left(\sum_{i\in I} \frac{emp_{s,i}}{emp_s} \times emp_{i,t}\right). \tag{16}$$

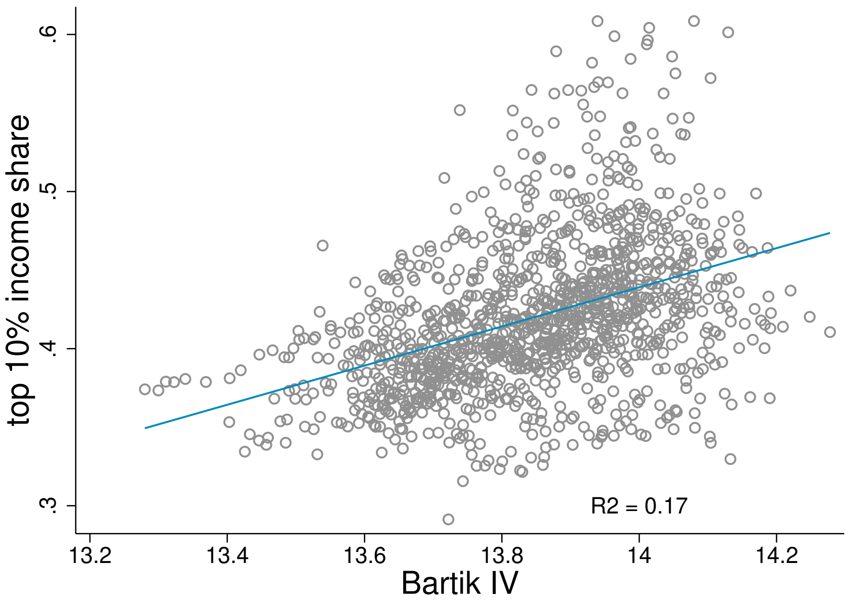
The BDS provide information on total employment for each of the top-30 4-digit industries i at the national level. To compute initial employment shares for each state-industry cell, we obtain data on the imputed County Business Patterns (CBP) from Eckert, Fort, Schott and Yang (2020). The strategy of 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 (2022) 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.

[35]In other words, the lion's share of the increase in earnings inequality arises because a handful of industries saw a stark increase in average earnings, while others saw a strong decline. Within-industry dispersion, i.e. some firms within a given industry paying increasingly more than others, plays a smaller role in explaining the overall increase in inequality.

Figure OA4 shows a strong and highly significant positive relation between top 10% income shares and our Bartik instrument. It provides a binned scatter plot at the state-year level of the Bartik-IV on the x-axis against the top-10% income share on the y-axis. There is a strong and positive correlation between the two variables ($t - value = 16, R^2 = 0.17$).

Figure OA4: **Bartik IV – first stage**



Note: This figure plots actual state-level top 10% income shares on the vertical axis and the Bartik IV on the horizontal axis.

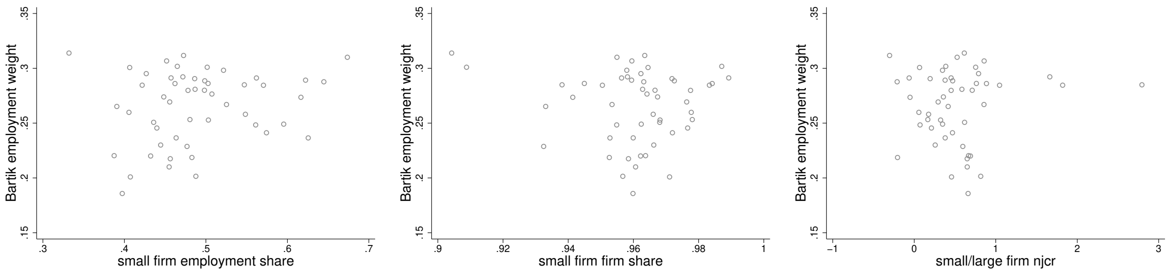
Similar to our IV based on pre-determined income shares, we verify that the initial employment share of the top-30 industries in a state is uncorrelated with the initial firm size distribution. As in Figure OA2, in Figure OA5 we plot the employment share of the top-30 industries in a given state on the 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.

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.[36]

[36]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.

Figure OA5: **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.

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 OA1 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 (16)). The mean (median) employment share is 1.1% (0.6%), with the 95^{th} and 99^{th} percentile equal to 4% and 7.2%.[37]

Table OA1: **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 (2022) 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

[37]These observations are in line with findings in Haltiwanger, Hyatt and Spletzer (2022), who also show that while these industries account for most of the rise in inequality, they account for only a modest share of overall employment. The industries with shares exceeding 5% on average are 4451 (Grocery Stores) and 6221 (General Medical and Hospitals). Code 7225 (Restaurants etc.) also has a fairly high share.

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.[38] We thus estimate the following regression at the state (s)-industry (i) level, but exclude these major industries from the analysis:

$$net\ jcr_{s,i,f,t} = \beta\ top\ 10\%\ income\ share_{s,t-1} \times small\ firm_f + \theta_{s,f} + \tau_{s,t} + \epsilon_{s,i,f,t}. \quad (17)$$

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 in these industries, since we exclude them from the analysis.[39] 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 OA2 and Table OA3 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.

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

[39]This way, we still exploit the effect of their presence on state-level inequality, but we exclude any confounding direct effect on employment at firms in a given state.

Table OA2: **Rising top incomes and job creation – pre-determined IV tests**

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	-	-	-	-	✓	✓

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. 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 columns. *** p<0.01, ** p<0.05, * p<0.1.

Table OA3: **Rising top incomes and job creation – Bartik IV tests**

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 Bartik IV. 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 columns. *** p<0.01, ** p<0.05, * p<0.1.

A.2 Further figures and tables for the empirical analysis

Figure OA6 provides additional details on the financial asset composition by household income. Figure OA7 provides direct evidence on household's liquidity needs by income. Figure OA8 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. This pattern reflects that high-income individuals generally have more resources to save.

Figure OA9 shows aggregate trends in deposits, loans, bonds and equities.

Figure OA10 presents the distribution of the share of banks' deposits and small business lending (based on data from the Community Reinvestment Act from 1997 to 2015) held outside banks' HQ state. It shows that only 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. Note that banks subject to CRA reporting requirements are generally larger, so the share of actual small business lending outside the headquarters states is likely overstated. Overall, these patterns show that banks fund themselves mostly through deposits in their HQ state, and also extend most of their small business loans in their HQ state.

Figure OA11 shows industries' small firm bank dependence.

Figure OA12 shows trends in the top 10% income share (black dashed line, right axis) and job creation of small firms (blue solid line, left axis) over time. While the top income share increases steadily, job creation of small firms is in secular decline.

Figure OA13 provides evidence on the occupations of top earners.

Table OA4 provides summary statistics for our main variables at the state and bank level, while Table OA5 provides summary statistics for SCF data. Table OA6 provides information on the net job creation rate, job creation rate, and small firm employment share by decade.

Table OA7 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 the results in Braggion, Dwarkasing and Ongena (2021). Finally, we move to state-industry-firm size-year level regressions. This has to advantages. First, relative to equation (1), the key difference is that 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. For example, rising import competition in some industries could affect firms in Ohio to a different degree than firms located in Nebraska. Similarly, we account for differential effects of changes in top incomes on all firms within a given industry in each state. Second, we can exclude non-tradable industries, thereby addressing the concern that rising top incomes induce changes in the local demand for good, which good affect the local industrial structure. Columns (6)–(8) report results for state-industry-firm size-year level regressions. Column (6) confirms that a rising top income share reduces job creation of small firms, relative to large firms. Similar to equation (1), column (6) includes state*size and state*year fixed effects to control for any unobservable changes within a given state-firm size cell and for common time-varying shocks at the state level. Column (7) 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 (6), indicating that unobservable trends that affect industries differentially within each state do not explain our findings. Finally, columns (8) focuses on firms in tradable industries only, and shows that also here, there is a negative effect of top income shares on job creation among small firms, relative to large.

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. Columns (1)–(4) show that rising top incomes affect job creation in bank-dependent industries by more both along the intensive and extensive margin. Columns (5)–(6) show that including state*industry*size fixed effects does not materially affect our estimates. With these fixed effects, we only exploit variation in how inequality affects the relative job creation of small firms within industries. This specification addresses the concern that states with rising top income shares see a shift in job creation towards larger firms in industries that are responsible for the rise on top income shares.

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.

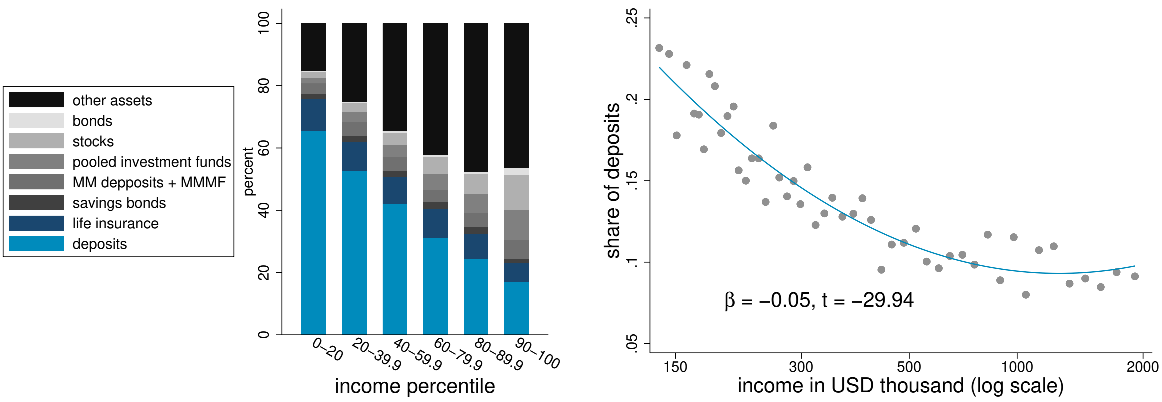
Table OA13 shows that the share of deposits in total financial assets declines in income, even after controlling for an extensive set of household characteristics.

Table OA14 provides additional evidence on bank deposits and loans by bank size.

Figure OA6: **More details on financial asset composition by income**

(a) Financial assets across income groups

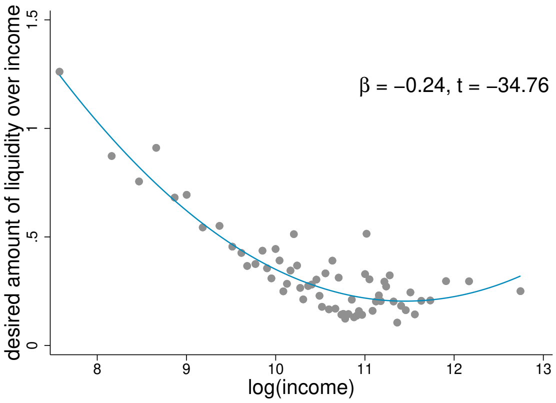
(b) Deposit share by income within top 10%



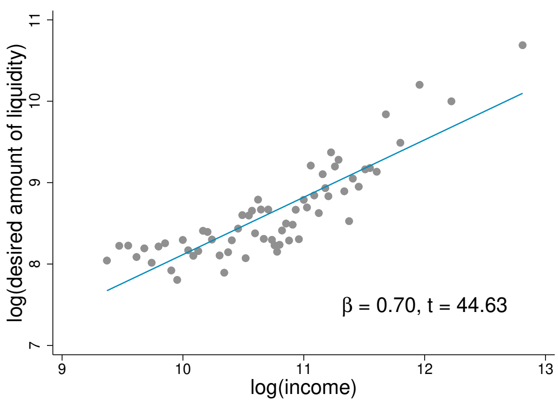
Note: Panel (a) provides a breakdown of the allocation of households' financial wealth by income group. Panel (b) provides a binned scatter plot with quadratic fit of the share of deposits over total financial assets on the vertical axis and log income on the horizontal axis for households with an income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

Figure OA7: **Direct evidence on household's liquidity needs by income**

(a) Desired liquidity share by income

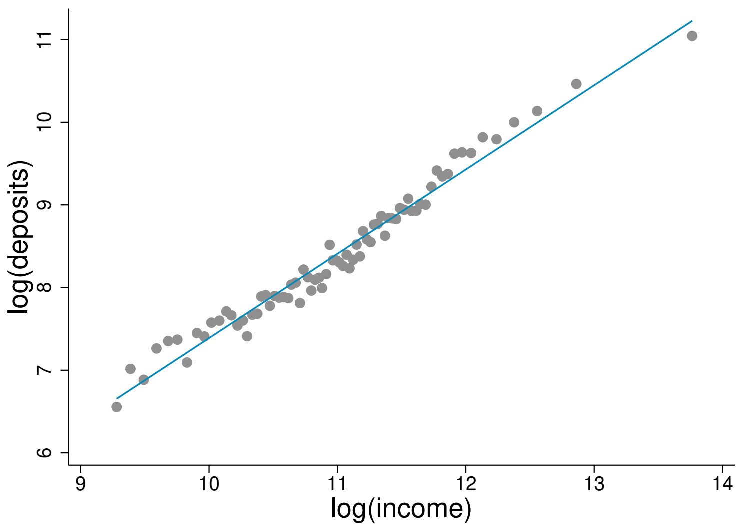


(b) Desired amount of liquidity by income



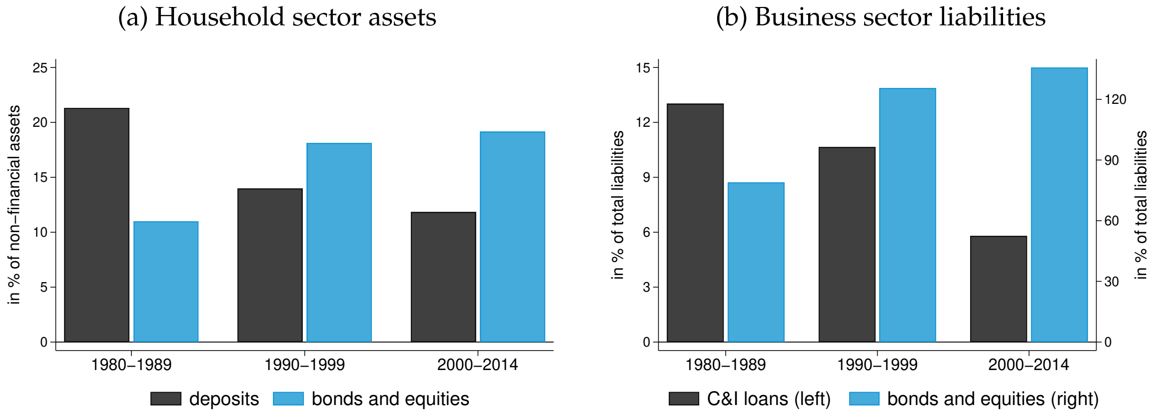
Note: Panel (a) provides a binscatter plot of the desired liquidity (defined as "About how much do you think you (and your family) need to have in savings for emergencies and other unexpected things that may come up?"), scaled by income, on the vertical axis and log income on the horizontal axis. Panel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

Figure OA8: **Household income and absolute deposit holdings**



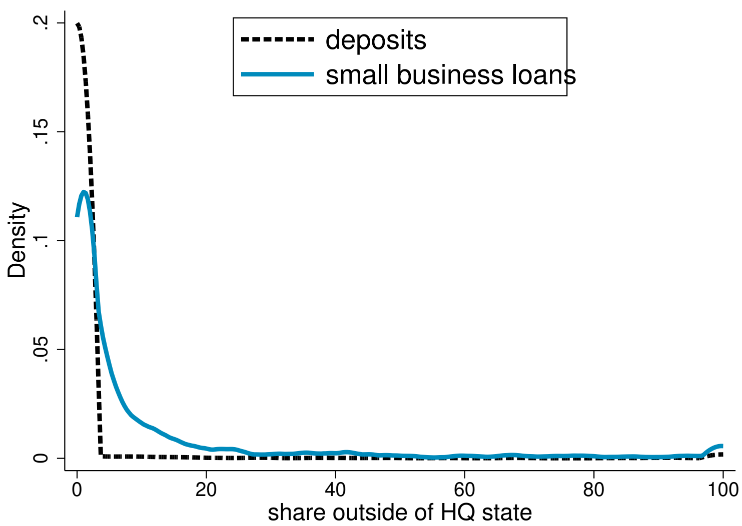
Note: Binned scatter plot with linear fit of the log of total household deposits (defined as the sum of checking accounts, savings accounts, call accounts and certificates of deposit) on the vertical axis and the log of total household income on the horizontal axis. Source: Survey of Consumer Finances.

Figure OA9: **Aggregate trends in deposits, loans, bonds and equities**



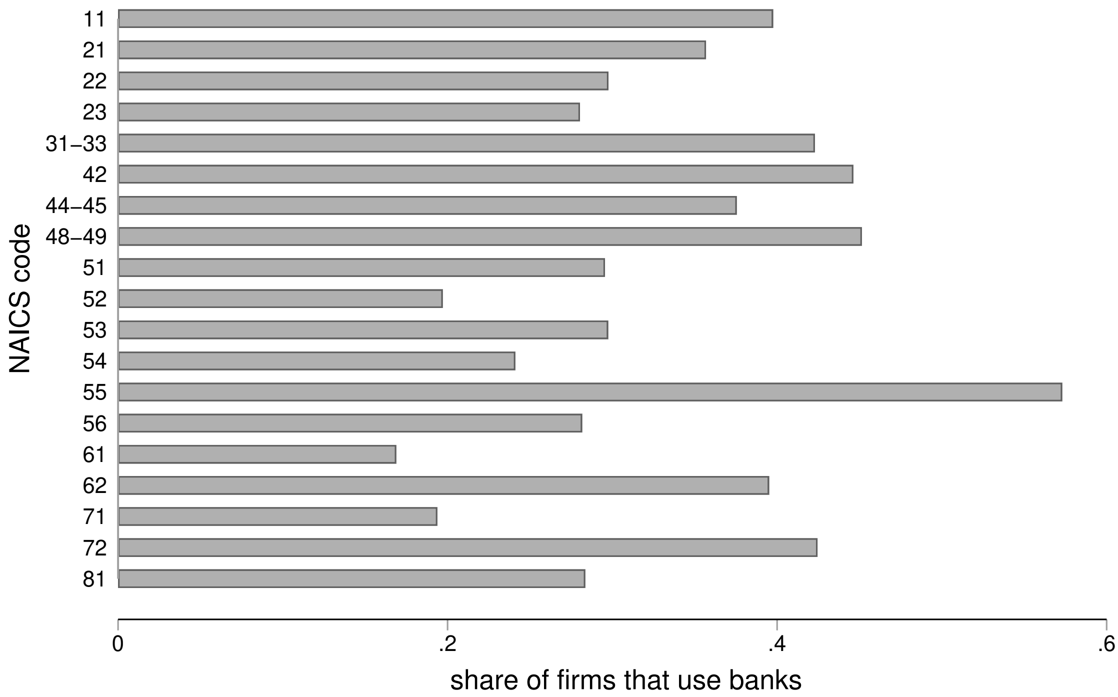
Note: Panel (a) plots deposits and bonds+equities as share of total household non-financial assets over time. Panel (b) plots C&I loans and bonds+equities as share of total non-financial corporate liabilities over time. Source: Financial Accounts of the United States.

Figure OA10: **Bank deposits and loans inside vs. outside headquarters state**



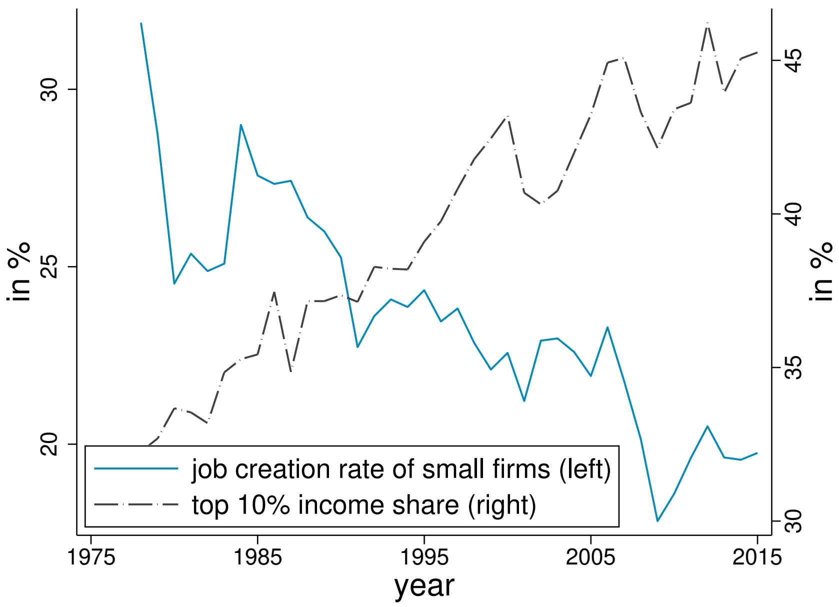
Note: Distribution of bank-year observations on the y-axis against the share of deposits held in branches located outside the banks' headquarters state (black dashed line) and the share of CRA small business loans originated to borrowers outside the banks' headquarters state (blue solid line) on the x-axis. Data is provided by the FDIC SOD, CRA, and US call reports.

Figure OA11: **Share of firms that use banks**



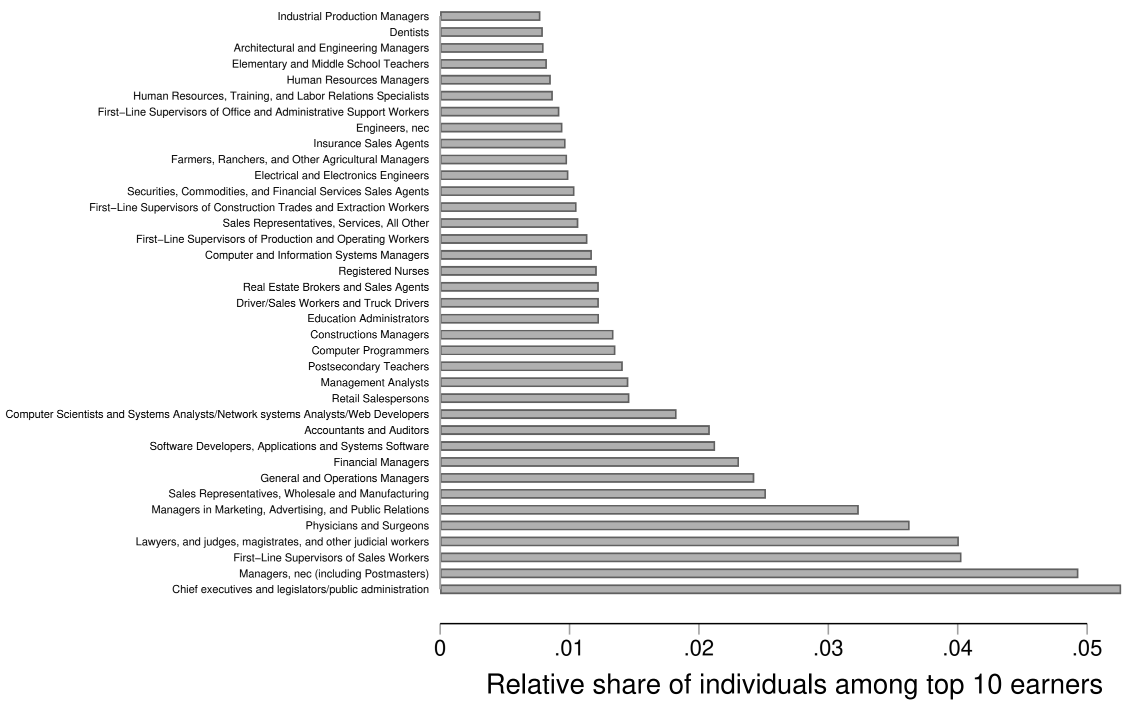
Note: Source is the Survey of Business Owners.

Figure OA12: **Top incomes and small business job creation over time**



Note: This figure shows the evolution of the top 10% income share, averaged across states, over time (black dashed line, left axis) and the evolution of job creation of small firms with 1-499 employees (blue solid line, right axis) over time. Source: Frank (2009) and BDS.

Figure OA13: **Who are the top earners? IPUMS occupations 2002**



Note: This figure lists all occupations that represent at least 0.75% of all top 10% income earners in 2002. Source: IPUMS.

Table OA4: **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	.935	.511	.013	3.254	.547	.931	1.291
log(C&I loans)	112884	9.535	1.712	0	14.787	8.421	9.446	10.575
C&I interest (in %)	112884	2.049	.991	0	22.463	1.469	1.859	2.378
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

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

Table OA5: **Descriptive statistics – 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 deppposits + 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 shows summary statistics for main variable from the Survey of Consumer Finances. For variable definitions and more details on the data sources, see the main text.

Table OA6: **Summary statistics by decade**

	net JCR	JCR	emp share
1980	3.3	21.7	53.8
1990	2.2	19.3	52.4
2000	.8	17.2	50.3
2010	1.8	15.3	48.5

Note: This table shows summary statistics for the net job creation rate, job creation rate, and employment share of small firms by decade. Source: BDS.

Table OA7: **Collateral, venture capital, public goods, and local demand**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		no boom states	no VC		edu sample			tradable
VARIABLES	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR
top 10% × small firm (1-499)	-0.136***	-0.143***	-0.163***	-0.292***	-0.593***	-0.213***	-0.225***	-0.291***
	(0.020)	(0.023)	(0.023)	(0.038)	(0.077)	(0.022)	(0.023)	(0.027)
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	192,968	192,968	155,589
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 in columns (1)–(5) and at the state-industry-firm size-year level in columns (6)–(8). 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. Column (6) estimates the baseline specification at the state-industry-firm size-year level with state*size and state*time fixed effects. Column (7) uses state*industry*time fixed effects instead of state*time fixed effects. Column (8) excludes non-tradable industries from the analysis. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Table OA8: **Alternative outcome variables**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		births	cont		deaths	cont					
VARIABLES	JCR	JCR	JCR	JDR	JDR	JDR	RAR	ln(emp)	ln(firms)	Δ JC	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. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

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

	(1)	(2)	(3)	(4)	(5)	(6)
	top 1%	no recession	no GFC	pre 2008	no boom years	
VARIABLES	net JCR	net JCR	net JCR	net JCR	net JCR	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 regression (1) 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**

	(1)	(2)	(3)	(4)	(5)	(6)
	low BD	high BD	low BD	high BD		
	extensive	extensive	intensive	intensive		
VARIABLES	net JCR	net JCR	net JCR	net JCR	net JCR	net JCR
top 10% × small firm (1-499)	-0.128***	-0.163***	-0.137***	-0.176***	-0.225***	-0.219***
	(0.019)	(0.019)	(0.025)	(0.022)	(0.023)	(0.023)
Observations	60,372	63,823	60,372	63,823	192,968	192,868
State*Size FE	✓	✓	✓	✓	✓	-
State*Industry*Year FE	✓	✓	✓	✓	✓	✓
State*Industry*Size FE	-	-	-	-	-	✓
F-stat	300.8	300.8	300.8	300.8	284.4	284.4

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**

	(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	0.031						
	(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**

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	-0.010						
	(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	-	✓	✓	-	✓
Time FE	-	-	-	-	-
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) log(dep)	(2) dep rate	(3) log(CI)	(4) CI rate	(5) state-level net JCR	(6) state-level net JCR
top 10% income share	-13.331***	-12.971***	-20.017***	-43.645***		
	(0.919)	(0.827)	(2.459)	(3.523)		
top 10% × log(assets)	1.352***	1.269***	1.783***	4.175***		
	(0.033)	(0.038)	(0.087)	(0.138)		
top 10% × very small firm (1-9)					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-level. *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. *** p<0.01, ** p<0.05, * p<0.1.

A.3 Additional details and results for structural model

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

Market clearing conditions

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

$$N_t = \int n_{i,t} di \tag{18}$$

$$\int \widetilde{n}^*_{j,t} dj = \int \widetilde{n}_{i,t} di, \tag{19}$$

where the left-hand side of both equations is labor demand and the right-hand side is labor supply. The integral over private firms' choices j is conditional on productivity being above the cutoff $\widetilde{z}$. The capital market clearing condition is

$$K_{t+1} = \int k_{i,t+1} di. \tag{20}$$

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

$$L_{t+1} = \int \left(\widetilde{f} + \phi \widetilde{w}_t \widetilde{n}^*_{j,t} \right) dj. \tag{21}$$

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

$$L_{t+1} = D_{t+1} = \int d_{i,t+1} di. \tag{22}$$

Finally, the goods market clearing condition is given by

$$Y_t + \int \widetilde{y}_{j,t} dj = C_t + I_t, \tag{23}$$

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 $\{c_i, n_i, \widetilde{n}_i, d_i, k_i, K, N, Y, \widetilde{y}_j, \widetilde{z}, \widetilde{n}_j, Pi_i, L, D, C, I, G, T_i\}$ 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 lifetime utility (4) subject to (5), taking $\{R_d, R_k, w, \widetilde{w}, \Pi_i, T_i\}$ as given.

2. The public firm's capital and labor demand satisfies the optimality condition (8) and (9). The public firm output is determined by (7).

3. Each private firm j chooses its cutoff productivity level $\underset{\sim}{z}$ and optimal employment $\widetilde{n}_j^*$ according to (12) and (13) for a given loan rate R_l. The output of private firm j is given by (10).

4. The loan rate is determined by (14) for 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 and private firm wage w and $\widetilde{w}$.

4. For given wages, capital stock, and the deposit rate, compute the public and private firm labor demand.

$$N = \left\{ \frac{(1-\theta)Z}{w} \right\}^{\frac{1}{\theta}} K \tag{24}$$

$$\widetilde{n}_j^* = \left[\frac{\alpha \widetilde{z}_j}{\{1 + (R_\ell - 1)\phi_j\}\widetilde{w}} \right]^{\frac{1}{1-\alpha}} \tag{25}$$

where

$$R_\ell = R_d + \frac{\Xi}{L} \quad \text{with} \quad L = \int \left(\widetilde{f} + \phi_j \widetilde{w} \widetilde{n}_j^* \right) dj \tag{26}$$

and the integral over j is conditional on $\widetilde{z}_j$ being above the cutoff $\underset{\sim}{z}$.

5. Check the labor market clearing conditions.

$$N = \int n_i di \tag{27}$$

$$\int \widetilde{n}_j^* dj = \int \widetilde{n}_i di \tag{28}$$

6. Iterate the step 3 to 5 until the labor market clears.

7. Compute R_k and Π.

$$R_k = \theta Z K^{\theta-1} N^{\gamma-\theta} + 1 - \delta \tag{29}$$

$$\Pi = \int \widetilde{\pi}_j dj + Y - R_k K - wN \tag{30}$$

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

9. Check the market clearing condition for deposit.

$$D = \int d_i di = L \tag{31}$$

10. Repeat steps 2 to 8 until the deposit market clears.
11. Check the capital market clearing condition.

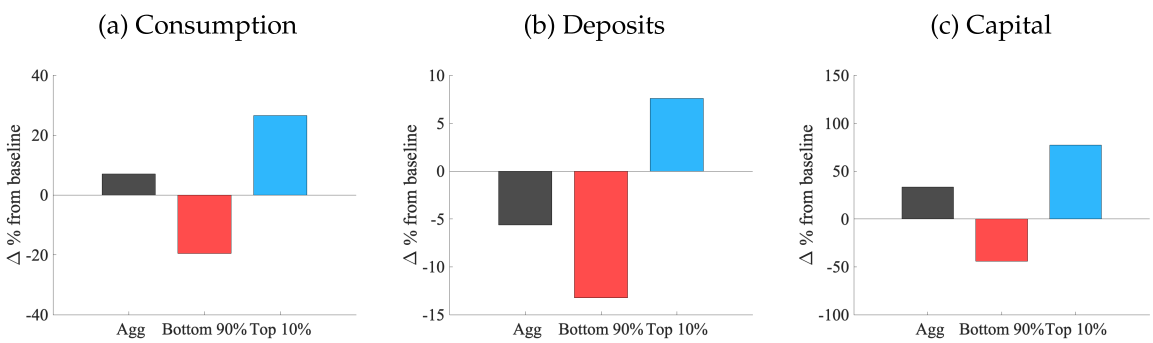
$$K = \int k_i di \tag{32}$$

12. 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 choice holding wages and returns constant. Figure OA14 plots the responses of consumption, bank deposits, and public firm capital to the redistribution scheme described above, 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 as well as savings in both deposits and public firm capital. Top earners, experiencing an increase in income, consume more and save more in deposits and capital.

Figure OA14: **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 OA14 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.

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 OA14 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). As an additional validation of our model, we study transitory income changes in the next section.

Discussion of MPC and MPS in the structural model

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 empirical 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, typically in Europe.[40] A relatively low MPC in the model can be attributed some features that the model abstracts from but that would likely give stronger consumption responses to transitory income changes. Examples from the literature are preference heterogeneity and the presence of illiquid assets.[41] The fact that deposits in our model play the role of a necessity good further reduces households' MPC.

Table OA15 presents MPCs and MPSs along the income distribution, and Table OA16 along the wealth distribution. 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.[42] Similarly, in our model, low income and low wealth households have higher MPCs than high income and high wealth households, though 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 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 relatively low income households.

[40] 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.

[41] 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.

[42] 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.

Table OA15: **MPC and MPS along the income distribution**

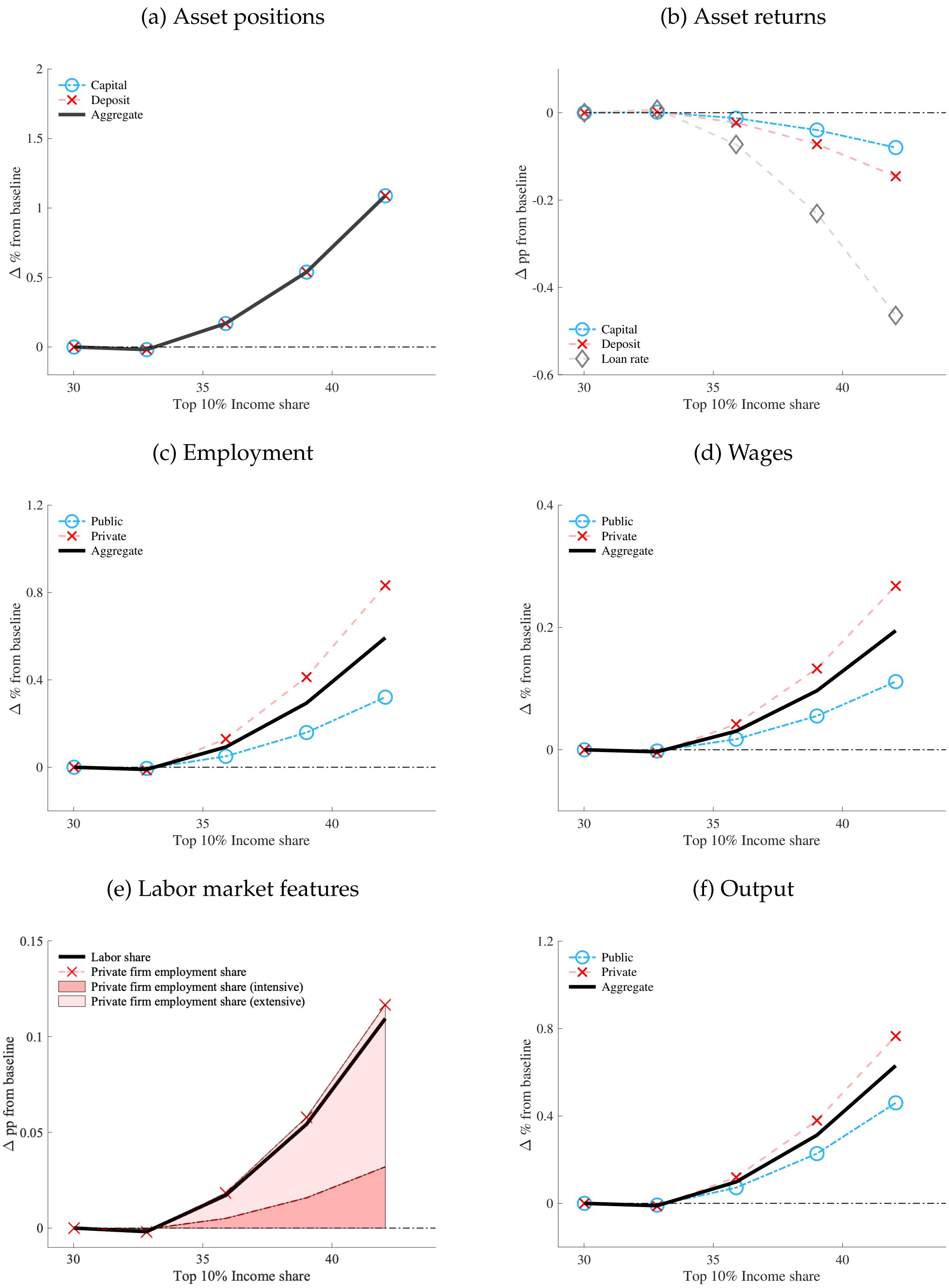
	MPC	MPS (deposit)	MPS (capital)
Q1	0.15	0.47	0.38
Q2	0.11	0.28	0.61
Q3	0.09	0.13	0.78
Q4	0.08	0.09	0.83
Q5	0.09	0.09	0.82
Bottom 90%	0.11	0.23	0.66
Top 10%	0.09	0.08	0.83
Average	0.11	0.21	0.68

Table OA16: **MPC and MPS along the wealth distribution**

	MPC	MPS (deposit)	MPS (capital)
Q1	0.13	0.35	0.52
Q2	0.08	0.09	0.83
Q3	0.08	0.08	0.84
Q4	0.08	0.07	0.85
Q5	0.08	0.06	0.86
Bottom 90%	0.11	0.23	0.66
Top 10%	0.08	0.05	0.87
Average	0.11	0.21	0.68

Additional results from the general equilibrium experiments

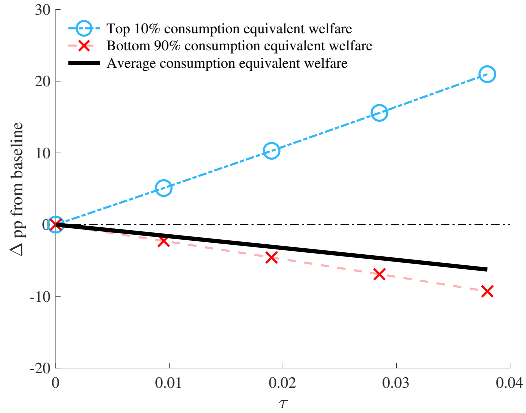
Figure OA15: **GE consequences of rising top income shares - Alternative model**



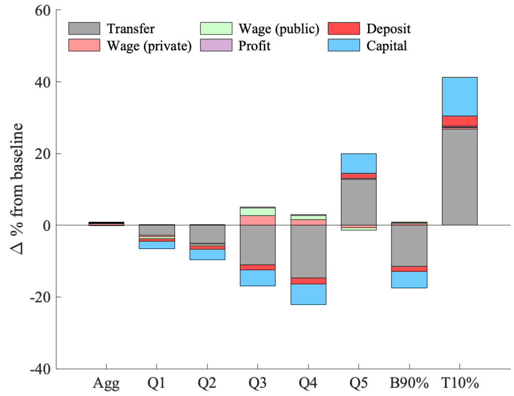
Note: This figure corresponds to Figure 3 in the main text, but shows the same results for the alternative model with fixed portfolio shares.

Figure OA16: **Welfare consequences - Alternative model**

(a) Welfare across households



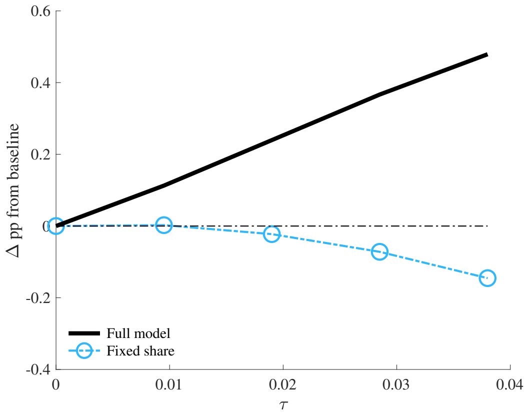
(b) Decomposition of income changes



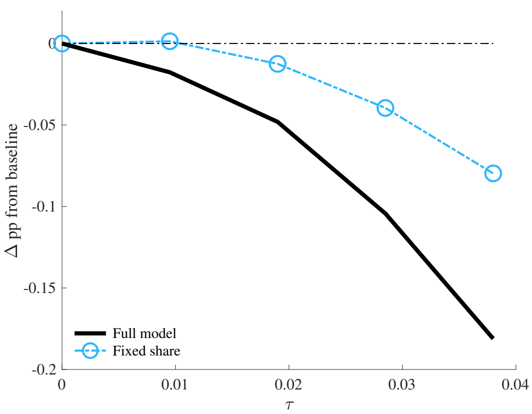
Note: This figure corresponds to Figure 4 in the main text, but shows the same results for the alternative model with fixed portfolio shares

Figure OA17: **GE consequences on prices across model versions**

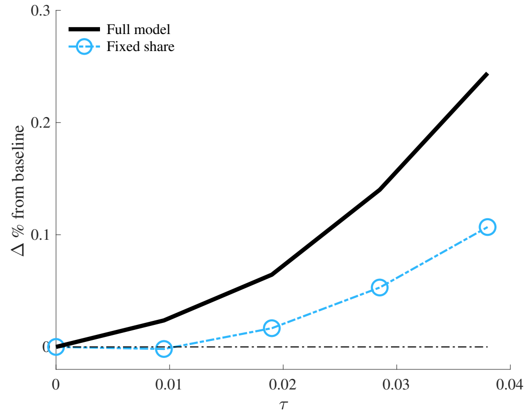
(a) Deposit return



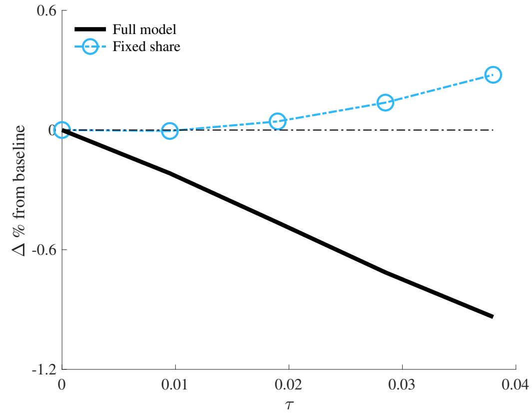
(b) Capital return



(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.