Private Innovation and Wealth Inequality[*,†]

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Abstract

Wealth inequality has risen sharply in recent decades. We study how restricted access to private-firm innovation contributes to this rise using a structural model of wealth accumulation with heterogeneous returns. Using a new long-run measure of innovation rents that includes both public and private firms, we document a pronounced shift in value creation toward private firms, whose equity is concentrated among high-wealth individuals. Calibrated to the 1979 wealth distribution, the model implies that exclusive access to private-firm innovation rents can account for between half and two-thirds of the subsequent increase in the top 1% wealth share.

JEL classification: D31, D52, E21, O31, G51
Keywords: Wealth inequality, Private markets, Innovation rents, Return heterogeneity

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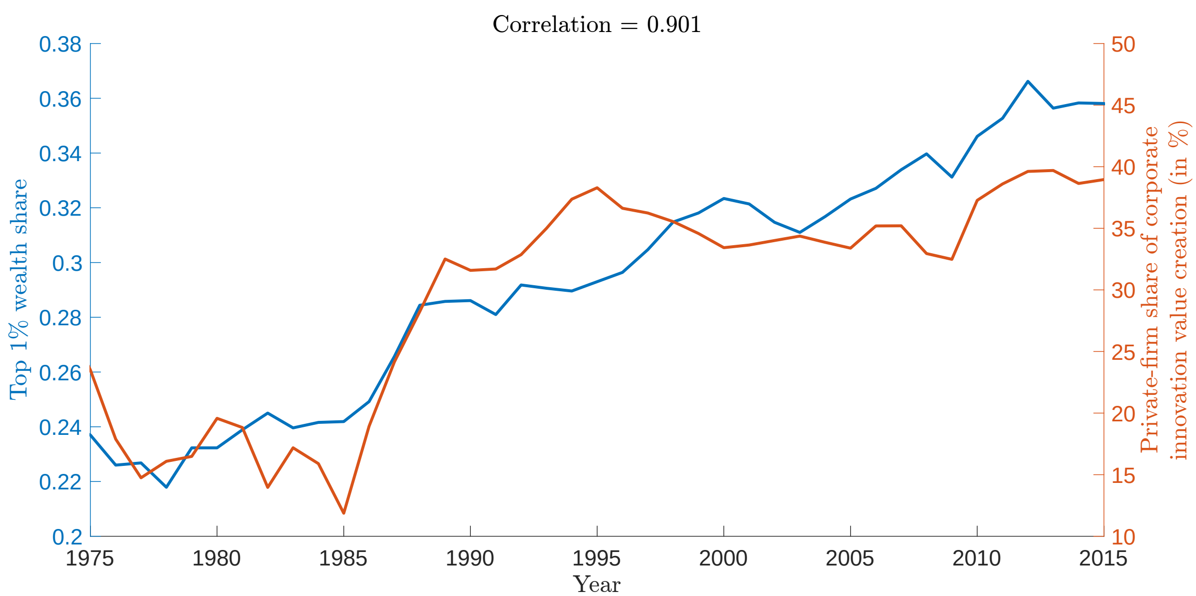
1 Introduction

Wealth inequality in the United States has risen sharply in recent decades. Between 1979 and 2015, the share of wealth held by the top 1% increased from 23.2% to 35.8%. Over the same period, a growing share of corporate innovation rents (measured as the capitalized value of patented inventions net of R&D costs) has been generated by firms not listed on public stock markets: the private-firm share more than doubled, from 16.5% in 1979 to 38.9% in 2015. As Figure I shows, the rise in the top 1% wealth share closely tracks this increase in the private-firm share of innovation rents (the time-series correlation is 90.1%). This paper asks whether, and to what extent, these trends are connected. In particular, we ask whether the rise in top wealth inequality is partly driven by a shift in innovation rents away from publicly traded firms, in which investment is broadly accessible, and toward private firms, in which investment opportunities are concentrated among high-wealth individuals.

Figure I: Wealth inequality and private-firm innovation rents



Note: The figure graphs the top 1% wealth share in the U.S. (on the left axis) and private U.S. firms' share of corporate innovation quasi-rents (on the right axis) between 1975 and 2015. Innovation rents are measured as the aggregate value of corporate patents (imputed from Kogan et al.'s (2017) estimates) net of R&D expenses (as measured by the NSF).

We address this question using a structural model of wealth accumulation with heterogeneous returns and a new long-run measure of innovation rents spanning both public and private firms. The key mechanism we study is exclusive access: high-wealth individuals disproportionately hold equity in private firms and therefore capture a larger share of the innovation rents generated in that sector.

As the locus of innovation shifts toward private firms, this unequal access creates a widening wealth-accumulation wedge between those at the top of the distribution and the rest. Quantitatively, after calibrating the model to match the 1979 wealth distribution and feeding in the observed evolution of innovation rents and the private share, we find that this mechanism can account for between half and two-thirds of the subsequent rise in the top 1% wealth share.

Our empirical starting point is a long-run macro measure of corporate innovation rents. We follow the patent-valuation framework of Kogan et al. (2017), which infers the value of each patent granted to a U.S. public firm from stock-market reactions around the grant date. To extend these valuations to private firms, we use the imputation model of Bias and Ljungqvist (2025), which relates patent values to observable patent characteristics in the spirit of Kline et al. (2019). Aggregating patent values across public and private firms yields an annual series of total innovation value back to 1975. Subtracting contemporaneous R&D spending then gives a macro measure of innovation rents. Scaled by aggregate household wealth, this series implies that innovation rents have contributed about 2 percentage points to annual wealth growth on average since 1975.

Our analysis builds on a central empirical fact: private firms account for an increasingly large share of corporate innovation rents. Using our long-run measure to decompose innovation rents by firm type, we find that private firms accounted for roughly 15% of innovation rents between 1975 and 1985, but that their share rose sharply from the mid-1980s onward and stabilized at around 35%–40% in 1995–2015. This shift is not driven by a growing number of private-firm patents. Rather, private-firm patents have become substantially more valuable relative to public-firm patents (Bias and Ljungqvist, 2025), and private firms now generate this value at lower R&D cost. As a result, a growing share of innovation rents is generated by private firms. Because ownership of and investment in innovative private businesses are highly concentrated among wealthy individuals (Cagetti and De Nardi, 2006; Bach, Calvet, and Sodini, 2020), this rise in the private share channels a growing fraction of aggregate innovation rents toward the top of the wealth distribution.

To quantify the implications of the shift in innovation rents toward private firms, we embed a single form of return heterogeneity into a dynamic wealth-accumulation model for the upper tail of the distribution (Gabaix et al., 2016; Hubmer, Krusell, and Smith, 2021). In the model, individuals who cross a wealth threshold receive an extra return component reflecting exposure to private innovation rents. Idiosyncratic wealth shocks generate mobility around the threshold, so access to this return premium changes endogenously over time. Our framework therefore isolates the role of exclusive access to private-firm innovation in shaping wealth dynamics. It yields a law of motion in which the upper tail responds not only to aggregate returns and economic growth—the standard "r minus g" channel—but also to the changing magnitude and exclusivity of innovation rents generated by private firms.

We calibrate the model to match the wealth distribution in 1979, when top concentration reached a historic low. We infer the common return from aggregate post-tax capital-income data. Guided by evidence from the Survey of Consumer Finances that private-business holdings are highly concentrated, our baseline specification assumes that only individuals in the top 1% have access to the additional return component associated with private-firm innovation. The time-varying wealth-accumulation wedge between high-wealth individuals and the rest is disciplined directly by our series on innovation rents (relative to aggregate wealth) and its private-firm share: larger innovation rents and a larger private share imply a larger wedge. The remaining free parameter—the subjective discount rate governing consumption behavior—is chosen so that the stationary wealth distribution implied by the model matches the observed top 1% share in 1979.

We then feed in the time series for innovation rents, the private-firm share of those rents, aggregate capital income and taxation, and economic growth from 1979 onward to simulate the wealth distribution through 2015. This exercise quantifies how much exclusive access to the rising private share of innovation rents contributes to the observed increase in the top 1% wealth share.

Our baseline quantitative results show that our model with exclusive access to private innovation rents for high-wealth individuals explains a large share of the observed rise in top wealth inequality. In the data, the top 1% wealth share increases from about 23% in 1979 to 36% in 2015, a rise of roughly 13 percentage points. Our model generates nearly 9 percentage points of this increase, accounting for about two-thirds of the empirical trend. By contrast, a standard wealth-accumulation model without exclusive access—in which all individuals earn the same average post-tax return—produces an increase of less than 1 percentage point over the same period. This stark divergence highlights the important role of private innovation rents, and of exclusive access to them, in the rise in top wealth concentration.

To assess the importance of the rising private share of innovation rents, we run a counterfactual in which this share is held fixed at its initial level of 16.5% in 1979. In this scenario, high-wealth individuals continue to receive, every year, the same fraction of innovation rents as in 1979, even as total innovation rents evolve over time. As a result, the wealth-accumulation wedge between high-wealth individuals and the rest increases only modestly. The counterfactual produces a rise of just 4 percentage points in the top 1% wealth share, compared with 9 percentage points in the baseline. The gap between these simulations shows that the increasing private share is a powerful amplification mechanism: without it, the model yields only a muted rise in top wealth inequality.

The analysis so far highlights the key role of exclusive access to private innovation rents in shaping wealth dynamics. We next examine how tax policy interacts with this mechanism. We find that policies affecting the taxation of capital gains and R&D subsidies have first-order effects on top wealth concentration, whereas taxes on interest income and dividends play a more limited role.

We conduct several robustness analyses to verify that our main result is not sensitive to the calibration of idiosyncratic risk, access thresholds, or within-top inequality targets, or to the measurement of innovation rents. For example, re-estimating the model to match inequality within the top 10% yields a nearly identical rise in the top 1% wealth share. Across all robustness exercises, our model continues to explain at least half the observed increase in the top 1% wealth share since 1979.

Related Literature. A large body of work studies the pronounced rise in U.S. wealth inequality in recent decades (Saez and Zucman, 2016; Piketty, Saez, and Zucman, 2018). A central explanation in quantitative macroeconomic models is heterogeneous returns to wealth. Benhabib, Bisin, and Zhu (2011), Benhabib and Bisin (2018), and Benhabib, Bisin, and Luo (2019) emphasize the role of saving behavior and return heterogeneity in shaping top wealth shares and intergenerational mobility. Hubmer, Krusell, and Smith (2021) combine several mechanisms—earnings heterogeneity, income-tax progressivity, discount-factor heterogeneity, and return heterogeneity—to account for the evolution of top wealth concentration. Gabaix et al. (2016) highlight how return heterogeneity, whether arising from exogenous type differences or scale dependence, affects the dynamics of inequality. Empirically, recent papers using micro data document that returns vary systematically across individuals and that this heterogeneity is sizable and persistent (Bach, Calvet, and Sodini, 2020; Fagereng et al., 2020). Using administrative data, Ebrahimian and Sodini (2024) estimate preference heterogeneity and show first-order implications for returns on wealth and intergenerational persistence.

We contribute to this literature by identifying and quantifying a specific, previously unmeasured source of return heterogeneity: exclusive access for high-wealth individuals to the value created by private-firm innovation. Our analysis is complementary to Gomez and Gouin-Bonenfant (2025), who show that lower required returns raise top wealth inequality by accelerating entrepreneurial capital accumulation; we instead focus on how unequal access to private innovation rents reallocates aggregate innovation rents toward the top of the wealth distribution. While existing work introduces return heterogeneity as a structural assumption or estimates it from micro returns, no study links it to differential access to a particular set of investment opportunities—namely, the innovation rents generated by private firms. Using our aggregate series on innovation rents and its decomposition by firm type, we show that this access-driven form of return heterogeneity has substantial explanatory power for the rise in top wealth inequality. Our focus differs from research on household portfolio heterogeneity and valuation channels (Greenwald et al., 2021; Catherine et al., 2023; Catherine, Miller, and Sarin, 2025): those papers study how time-varying asset yields affect valuations, whereas we examine heterogeneity in access to a source of value creation itself—innovation by private firms.

A narrower line of empirical research has examined individuals' investment in private markets and its implications for inequality. Canipek (2024) studies investment behavior around the "accredited-investor" eligibility cutoff,[1] while Gocmen, Martínez-Toledano, and Mittal (2025) analyze how capital-gains taxation affects high-net-worth individuals' investment in early-stage companies and their realized returns. Our analysis differs in two important ways. First, we are not concerned with a particular regulatory threshold or a specific segment of the private market. Instead, we aggregate the full value of private-firm innovation in the U.S. economy and quantify the extent to which access to this value creation is concentrated among wealthy individuals. Second, we embed this access mechanism into a structural, economy-wide model of wealth accumulation and show that it has first-order implications for the rise in top wealth concentration.

Our mechanism differs from the classic entrepreneurship channel in Quadrini (1999) and Cagetti and De Nardi (2006), which features return heterogeneity through occupational choice. In those mod-

[1] Lindsey and Stein (2019) analyze angel investment under the accredited-investor definition, but focus on firm outcomes rather than investors' wealth accumulation.

els, wealth concentration arises because entrepreneurs earn higher returns than workers, reflecting differences in productivity, risk, or borrowing constraints. This is a cross-sectional mechanism explaining why wealthy individuals hold private businesses. By contrast, our mechanism operates through a time-series shift in where innovation rents are generated. We show that the share of innovation rents created by private firms has increased sharply since the 1980s, even as the concentration of private business ownership has remained broadly stable. In a standard entrepreneurship model, a constant private-business share would imply stable inequality. In our setting, however, the reallocation of innovation activity toward private firms raises wealth concentration because it shifts the locus of value creation toward assets disproportionately held by the wealthy. Thus, we do not rely on entrepreneurs earning higher intrinsic returns; instead, inequality rises because the economy increasingly generates innovation rents in a sector less accessible to the population.

In summary, we assemble a new long-run measure of corporate innovation rents that, for the first time, covers both public and private firms. We document a sharp rise in the share of innovation rents generated by private firms—a shift that Bias and Ljungqvist (2025) show is driven by the increasing economic value of private-firm patents. We build a structural model in which access to this private-firm innovation value is limited to high-wealth individuals, calibrate it to the U.S. wealth distribution in 1979, and show that this access mechanism can account for a substantial share of the subsequent rise in top wealth inequality. Our framework thus highlights a new channel through which the organization of corporate innovation—particularly its movement outside public markets—feeds into wealth concentration at the top. This channel is complementary to others emphasized in the literature (such as savings behavior, entrepreneurial dynamics, earnings heterogeneity, and tax progressivity) that may also contribute to the evolution of wealth inequality.

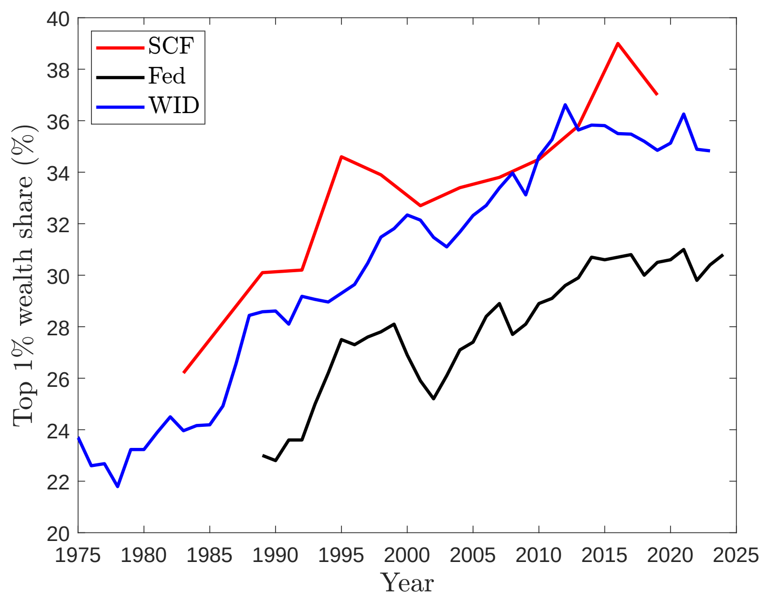
The remainder of the paper is organized as follows. Section 2 introduces the data and documents the evolution of corporate innovation rents and the private innovation share. Section 3 presents the model, and Section 4 describes its estimation, calibration, and simulation. Section 5 reports the baseline results and counterfactuals, and Section 6 provides robustness checks. Section 7 concludes.

2 Data and Facts

2.1 The Rise in Wealth Inequality

Wealth inequality in the United States has increased markedly over the past several decades. Figure II plots the top 1% wealth share using three widely used sources: the Survey of Consumer Finances (SCF), the Federal Reserve's Distributional Financial Accounts (DFA), and the World Inequality Database (WID).[2] Despite differences in levels, all three sources show a pronounced rise in top wealth concentration. In the WID series, for example, the top 1% share increased from about 23% in 1979 to 35% in 2023.

Figure II: Wealth inequality



Note: The figure plots the top 1% wealth share using data from three sources: the Survey of Consumer Finances (SCF), the Federal Reserve DFA Survey, and the World Inequality Database (WID).

2.2 A Macro Measure of Corporate Innovation Quasi-Rents

We construct a macro measure of corporate innovation quasi-rents, defined as the value of newly created patented inventions net of contemporaneous R&D expenditures. The construction proceeds

[2] The SCF provides survey-based estimates of household wealth. The DFA combines SCF microdata with national accounts to incorporate components of wealth that are poorly captured in surveys, such as defined-benefit pensions, annuities, and insurance reserves (Batty et al., 2021). The WID series derives wealth estimates from administrative income tax data using a structural mapping between capital income and asset holdings. Because it offers consistent coverage over a longer horizon, our analysis primarily relies on the WID data.

in three steps. First, we estimate the value of patents granted to public firms using stock-market reactions. Second, we impute the value of patents granted to private firms based on observable patent characteristics. Third, we aggregate patent values across all firms and subtract aggregate corporate R&D spending to obtain a measure of innovation rents at the macro level.

Our sample period runs from 1975 to 2015. The start date is dictated by the availability of reliable R&D data for public firms, while the end date reflects data availability for key variables used in the imputation model.

Patent values for public firms. We follow Kogan et al. (2017) in estimating the value of patents granted to public firms using stock price movements around the patent grant date (suitably scaled to recover the full patent value rather than only the announcement surprise). Intuitively, these estimates capture the market's assessment of the change in the present discounted value of future profits induced by the innovation. We interpret them as measuring the capitalized quasi-rents generated by innovation, prior to accounting for R&D costs.

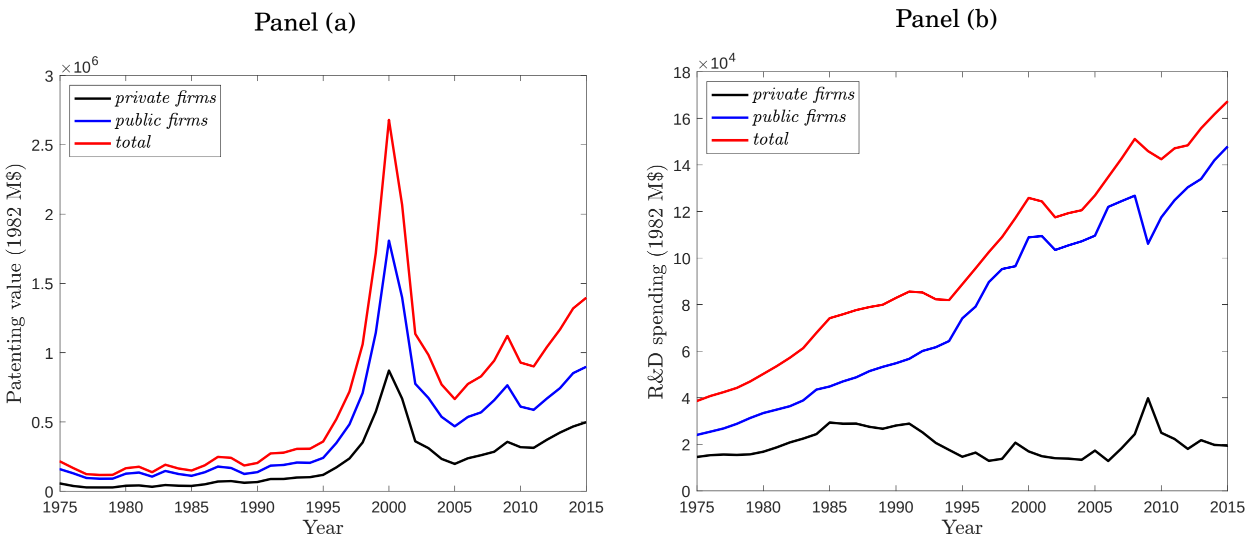
Implementing this approach requires identifying patents granted to U.S. public firms. We use the patent–firm linking table compiled by Bias and Ljungqvist (2025), which refines and extends the latest linking table of Kogan et al. (2017).[3] Using this updated linkage, we reestimate the Kogan et al. (2017) valuation model for our sample.

Patent values for private firms. To estimate the value of patents granted to private firms, we adopt the imputation approach of Kline et al. (2019) as implemented in Bias and Ljungqvist (2025). The model relates public-firm patent values to observable patent characteristics that proxy for economic value, including forward citations, the number of independent claims, generality and originality (Trajtenberg, Rebecca, and Jaffe, 1997; Hall, Jaffe, and Trajtenberg, 2001), as well as indicators for breakthrough and strategic patents (Kelly et al., 2021; Veihl, 2022). To allow for time variation in the valuation of these characteristics, the model is estimated recursively over rolling 10-year windows using a Poisson specification with grant-year and technology-class fixed effects. The fitted values from this model provide imputed patent values for private firms.

[3] Two refinements are particularly relevant for our sample. First, using corporate ownership trees from the National Establishment Time Series (NETS), Bias and Ljungqvist (2025) identify patents granted to subsidiaries of public firms from 1989 onward, capturing patents assigned to subsidiaries whose names differ from those of their publicly listed parents. Second, they correct misclassifications in existing linking tables, reclassifying a large number of patents across public and private firms and correcting erroneous CRSP permco links.

Aggregation and innovation rents. Figure III, Panel (a), plots the aggregate value of patents granted to U.S. firms from 1975 to 2015, in constant 1982 dollars. Aggregate patent values fluctuate over time, with a pronounced increase in the late 1990s and persistently elevated levels thereafter. Public and private firms exhibit broadly similar time-series patterns.

Figure III: Patent values and R&D spending



Note: Panel (a) plots the aggregate imputed value of patents granted to U.S. firms, as well as the corresponding values for public and private firms, in constant 1982 dollars. Panel (b) plots aggregate corporate R&D spending by U.S. firms and its decomposition into public and private firms. Data on private firms' R&D spending are not available before 1975.

To obtain innovation rents, we subtract the flow cost of R&D from aggregate patent values. We measure total corporate R&D spending using data from the National Science Foundation (NSF).[4] Since public firms have been required to disclose R&D expenditures since the mid-1970s, we measure their R&D directly from Compustat. We then infer private-firm R&D as the difference between total corporate R&D and public-firm R&D.

Figure III, Panel (b), plots aggregate R&D spending by public and private firms. While R&D spending by public firms has grown steadily, private-firm R&D has declined in relative terms. As a result, private firms account for a shrinking share of corporate R&D expenditures even as their share of patent value rises. This divergence implies a substantial increase in the contribution of private firms to innovation rents.

Measurement concerns. Two measurement concerns are worth noting. First, our inference relies

[4]The latest release is available from the National Center for Science and Engineering Statistics.

on estimates of private-firm R&D constructed residually from aggregate data. Measurement error could therefore affect the evolution of innovation rents. In Section 6.4, we show that our results are robust to alternative assumptions that eliminate the implied rise in private-firm R&D efficiency in Figure III, Panel (b).

Second, while imputation procedures like the one we use to estimate private-firm patent values have a long history in economics, their performance remains an empirical question. Validation exercises in Kline et al. (2019) (in-sample) and Bias and Ljungqvist (2025) (out-of-sample) indicate strong fit, with actual and imputed values closely aligned along the 45-degree line (slopes of 1.03 and 1.01, respectively). Nonetheless, one may be concerned that private-firm patents are systematically valued differently from public-firm patents. In Section 6.4, we show that our findings are robust to applying conservative haircuts to private-firm patent values.

In the next subsection, we decompose innovation rents by firm type and construct the private share of innovation, which plays a central role in our analysis. We note that the rise in the private share documented in Figure I is also supported by alternative measures that do not rely on imputed patent values (Bias and Ljungqvist, 2025).

2.3 Private Firms' Share of Innovation Rents

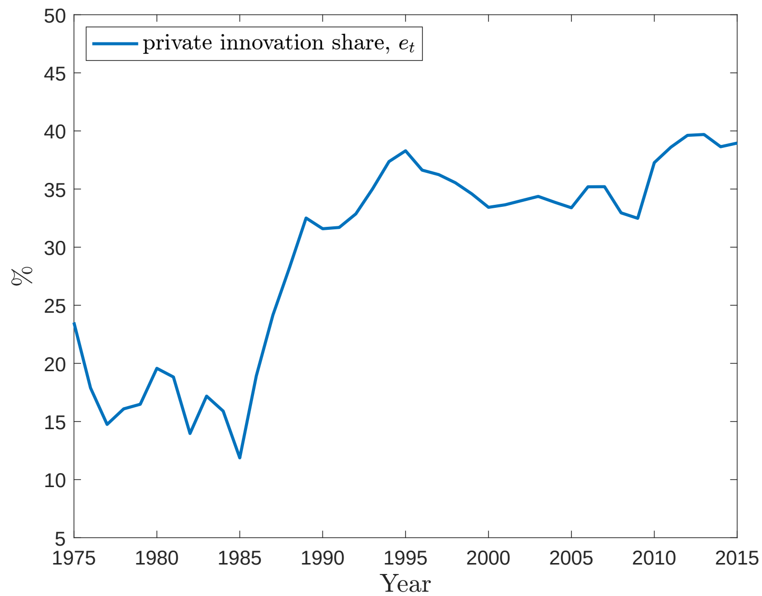
Our central object is the share of innovation rents generated by private firms. This share captures the extent to which the rents created by corporate innovation accrue in segments of the economy that are largely inaccessible to broad household investment. We measure this object as the fraction of aggregate innovation rents accounted for by private firms. Concretely, we define e_t as the ratio of innovation rents generated by private U.S. firms to total corporate innovation rents in year t.[5] We refer to e_t as the *private innovation share*.

Figure IV plots e_t over the period 1975-2015. The private innovation share declines from 23.5% in 1975 to 11.9% in 1985, then rises sharply—more than tripling to 38.3% by 1995—and remains elevated thereafter, fluctuating between roughly 32% and 40%. Thus, at least one-third of the value created by corporate R&D in the U.S. since the mid-1990s has accrued exclusively to those individuals

[5] Our results are robust to alternative constructions that combine observed patent values for public firms with imputed values for private firms.

who have access to, and can invest in, private firms.

Figure IV: The private innovation share



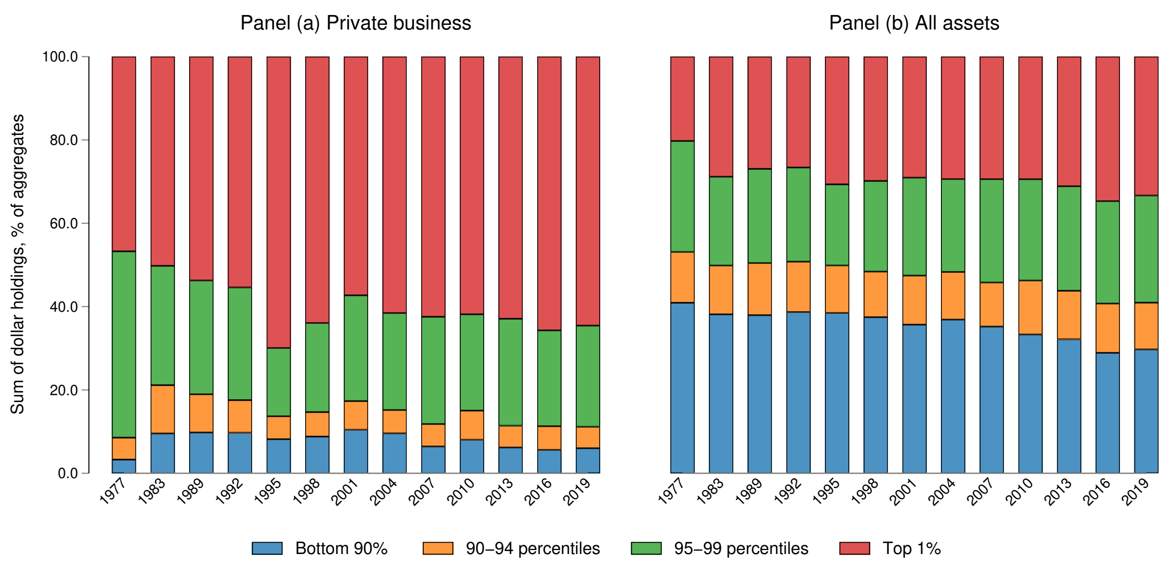
Note: The figure plots the time series of the private innovation share, e_t, defined as the share of the value of private U.S. firms' patents in the aggregate value of U.S. corporate patents, each net of R&D spending. Data on private firms' R&D expenditures are not available before 1975.

What drives the rise in the private innovation share? In principle, e_t could increase either because private firms produce a larger number of patents or because they produce more valuable innovations. The evidence points strongly to the latter. As Bias and Ljungqvist (2025) document, private firms' share of patent counts has remained remarkably stable—at around 30%—since the 1970s. The increase in e_t instead reflects a reallocation of innovative activity toward technologies with higher economic value, in which private firms have become increasingly dominant. In particular, private firms—especially younger and venture-backed firms—have shifted R&D toward fields with rising valuations, allowing them to capture a growing share of aggregate innovation rents despite stable patent shares. For our purposes, this shift implies that the location of value creation—not just its aggregate level—has become a key determinant of who captures the gains from innovation.

2.4 The Concentration of Private-Business Equity

Ownership of, and investment in, private businesses is extremely concentrated in the United States. Figure V plots the shares of private-business equity (Panel a) and total assets (Panel b) held by four groups: the top 1%, households in percentiles 95–99, households in percentiles 90–94, and the bottom 90% of the wealth distribution. The data come from the SCF and SCF+ (Kuhn, Schularick, and Steins, 2020) for 1977–2019 and cover both active and passive private-business holdings. Active holdings include a wide range of privately held firms, from sole proprietorships and professional practices to founders' equity stakes in their start-ups.

Figure V: Private-business equity, by net-wealth percentile



Note: The figure plots the shares of private-business equity (in Panel a) and total assets (in Panel b) that are held by four groups of households: the top %1, households in percentiles 95-99, households in percentiles 90-94, and the bottom 90% of the wealth distribution. The data come from the SCF Summary Extract Public Data (1989 onward) and SCF+ for earlier years (Kuhn, Schularick, and Steins, 2020)

The figure shows that the top 1% consistently hold the majority of private-business equity in every SCF wave, and this share has remained remarkably stable over time. The top 5% collectively hold more than 80% of private-business equity. By contrast, the bottom 90% hold less than 10%, a small and declining share that presumably largely reflects self-employment businesses rather than investments in innovative private firms.

Importantly, this concentration is not simply a reflection of the overall concentration of wealth. As shown in Panel (b) of Figure V, total assets are far less concentrated. Consistent with Figure II, the top 1% hold roughly 25–35% of aggregate assets—only about half of their share of private-business equity. Thus, high-wealth households hold a disproportionately large fraction of their portfolios in private-business equity.[6]

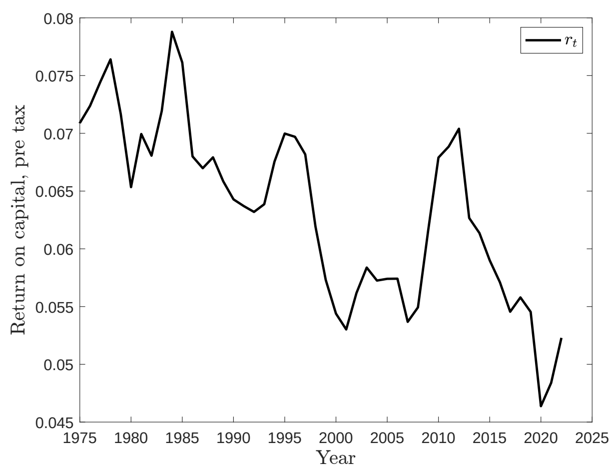
The high concentration of private-business equity implies that any increase in private firms' innovation rents will necessarily channel a growing share of aggregate innovation rents to the top of the distribution. Section 3 develops a structural model to quantify this mechanism.

2.5 Other Data

2.5.1 Aggregate Return on Capital

We construct the average annual pre-tax return on capital, r_t, following Piketty and Zucman (2014). Specifically, we measure r_t as $r_t = \theta_t/\beta_t$, where θ_t is the capital share of national income and β_t the wealth-to-income ratio. To estimate θ_t and β_t, we use data from the Integrated Macroeconomic Accounts (IMA) maintained by the Federal Reserve and the National Income and Product Accounts (NIPA) maintained by the Bureau of Economic Analysis. The capital share of national income, θ_t, is computed as total capital income (corporate profits, housing capital income, self-employment capital income, net foreign capital income, and net government interest payments) divided by national income. The wealth-to-income ratio, β_t, is obtained by dividing net private wealth (financial and non-financial assets, net of financial liabilities) by national income.[7] Figure VI graphs r_t over our sample period, beginning in 1975.

Figure VI: Average pre-tax return on capital



Note: The figure plots the average pre-tax return on capital, r_t, since 1975.

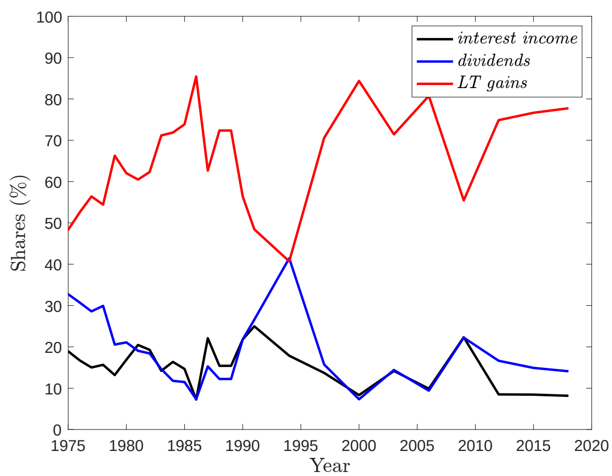
[6]Table A.1 reports the corresponding dollar values across wealth groups and SCF waves.
[7]See Section A.1 in the Appendix for details.

2.5.2 Capital Income Taxes

Our measure of personal taxes on capital income departs from the literature by combining a focus on *marginal* tax rates (those applying to the top of the income distribution) with consideration of the different components of capital income: interest income, dividends, and capital gains. As we will show, distinguishing between these components turns out to be important for two reasons. First, long-term capital gains and the taxes due on them are the most relevant to understanding the evolution of wealth for the top 1%. Second, marginal tax rates on interest income, dividends, and capital gains differ greatly from each other and vary considerably over time.[8]

Figure VII graphs the shares of total capital income that the top 1% receive from interest, dividends, and long-term capital gains, respectively.[9] Long-term capital gains are consistently and by far the largest source of capital income in every year since 1975, while interest income is almost always the smallest source (with dividends in between). To illustrate, in 1979, the top 1% received as much as 66% of their total capital income from long-term capital gains and only 13% from interest income.

Figure VII: Capital income shares

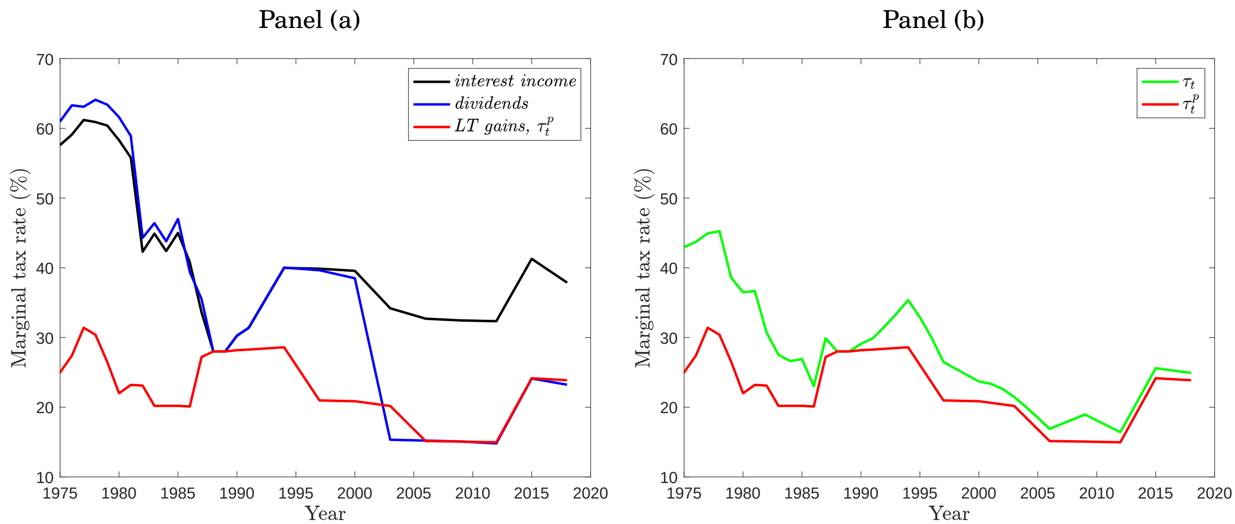


Note: The figure graphs the shares of various capital income components in total capital income, which we use as weights to compute the overall marginal tax rate. The data are smoothed using 3-year moving averages. Before 1989, the data source is WID, with minor adjustments to long-term capital gains; from 1989 onward, capital income shares are calculated using the SCF dataset.

[8]Moreover, the U.S. applies different tax rates to capital gains on short-term investments (those held for less than a year) and long-term investments (those held for more than a year). There are at least three reasons why patent-related capital gains would usually be taxed at the long-term capital gains rate in our setting: investments in R&D typically take a long time to bear fruit; once it has, obtaining a patent usually takes at least a year (and often longer); and private firms are illiquid, meaning an investor cannot sell their shares in private firms at will, which tends to increase holding periods.

[9]For details on how we construct each of the series discussed in this section, see Section A.2 in the Appendix.

Figure VIII: The top 1%'s marginal tax rates on capital income



Note: Panel (a) plots the top 1%'s marginal tax rates on the three main components of capital income: interest income, dividends, and long-term capital gains. (We ignore short-term capital gains, which account for no more than a few percent of capital income, because the required data are not available before 1989.) Panel (b) plots the weighted-average marginal tax rate on capital income, τ_t (using the capital income shares shown in Figure VII as weights), alongside the marginal tax rate on long-term capital gains, τ_t^p, from Panel (a). All tax rates and shares are smoothed using 3-year moving averages. Before 1989, estimates of marginal capital-income tax rates are from Feenberg and Coutts (1993); from 1989 onward, they are obtained from TAXSIM using SCF data as inputs.

Figure VIII, Panel (a) graphs the marginal tax rates on each component of capital income. To estimate these tax rates, we follow Auerbach and Hassett (2015) and others and use the TAXSIM model maintained by the National Bureau of Economic Research (NBER).[10,11] Except in 1988, when all components of capital income are briefly taxed at the same rate, taxes on long-term capital gains are on the order of 15-30 percentage points lower than taxes on interest income; before the Jobs and Growth Tax Reconciliation Act of 2003, they are also lower than taxes on dividends.

Collectively, Figure VII and Figure VIII show that using the marginal tax on interest income to compute the after-tax return of the top 1% (as is done in, e.g., Auerbach and Hassett, 2015) is misleading for two reasons: the top 1% derive most of their capital income from long-term capital gains, and long-term capital gains are taxed at a much lower rate than is interest income. Moreover,

[10]For details on TAXSIM, see Feenberg and Coutts (1993).

[11]TAXSIM simulates an individual's marginal tax rate on each component of capital income when fed the individual's data on labor income (including pension and business income), capital income (i.e., interest income, dividends, and short-term and long-term capital gains), and deductions. A practical consideration arises because the relevant input data are available in the Survey of Consumer Finances (SCF) only from 1989 onward. For the period from 1975 to 1988, we use Feenberg and Coutts' (1993) estimates of marginal tax rates based on tax returns filed with the Internal Revenue Service. Because Feenberg and Coutts focus on the top 1% of the *income* rather than the *wealth* distribution, our TAXSIM simulations after 1989 use SCF data for the top 1% by income. Figure A.3 in the Appendix shows that at least after 1989, marginal capital income tax rates are very similar in the top 1% of the income and wealth distributions.

the dynamics of marginal tax rates on interest and on long-term capital gains are very different: while the former have generally fallen over time, the latter have been much more stable.

Our model simulations in Section 4 use two tax rates: the marginal tax rate on long-term capital gains, denoted τ_t^p, and the weighted average marginal tax rate on capital income, denoted τ_t. The latter uses as weights the capital income shares of the top 1%, plotted in Figure VII. Figure VIII, Panel (b) graphs the two tax-rate series.

3 Model

We build on the models for the dynamics of inequality presented by Gabaix et al. (2016) to study the evolution of top wealth inequality. We include return heterogeneity by considering exclusive access for wealthier individuals to private innovation rents.

Denote by w_{it} individual i's wealth at time t. Every individual receives a common return on her wealth in period t, which we call the "market return" and denote by r_t^m. We can think of r_t^m as the return generated by broadly accessible investments, such as publicly traded firms. Individuals whose wealth w_{it} is sufficiently high (to be specified shortly) have exclusive access to an additional investment technology that raises their wealth accumulation rate by Δ_t. We interpret this additional component as the return associated with access to private-firm innovation rents.[12]

Individuals also experience idiosyncratic shocks to the return on their wealth, denoted by σdZ_{it}, where σ is the standard deviation of the shock and dZ_{it} is *iid* across individuals and time. The rate of return on wealth thus varies across individuals because *some* individuals have exclusive access to Δ_t and because individuals experience different shocks dZ_{it}; it also varies over time because both r_t^m and Δ_t vary over time. We consider all these terms to represent *after-tax* returns.

In the baseline model presented in this section, we consider a form of return heterogeneity in which an individual has access to Δ_t if and only if her wealth w_{it} exceeds $\bar{w}_t$, which we call the "access cutoff." In the generic representation, this threshold may vary over time. In our simulations in Section 5, it is set flexibly, either at the 99th wealth percentile at each point in time (corresponding

[12] Investors in private firms purchase equity claims on entire firms, not innovation rents in isolation. Accordingly, Δ_t captures the incremental return component associated with private-firm innovation, while the remainder of firm returns is absorbed into the common market return r_t^m.

to only the top 1% having access to Δ_t) or at a fixed value in absolute terms over time (reflecting, for example, regulatory criteria defining "accredited investors" permitted to invest in private companies). Later in Section 6, we also explore cases with multiple cutoffs, modeling individuals with heterogeneous (and potentially partial) access to Δ_t.

All individuals earn the same deterministic labor income y_t, which grows at the rate g_t over time. In our setup, labor income serves only as the stabilizer of the wealth distribution.[13] At each point in time, an individual consumes at a rate proportionate to her wealth: $c_{it} = \rho w_{it}$, where ρ represents the time discount rate in individuals' preferences. This consumption policy can be micro-founded by considering a unit elasticity of intertemporal substitution (EIS),[14] when ignoring human capital in total wealth, as is reasonable for individuals at the top of the wealth distribution.

The individual's wealth accumulation follows

$$dw_{it} = y_t dt - \rho w_{it} dt + (r_t^m + \mathbf{1}\{w_{it} \geq \bar{w}_t\}\Delta_t) w_{it} dt + \sigma w_{it} dZ_{it}, \tag{1}$$

where the indicator function $\mathbf{1}\{w_{it} \geq \bar{w}_t\}$ represents the criterion for exclusive access to Δ_t. By definition, Δ_t is the difference in the wealth accumulation rate between those whose wealth is above and below the access cutoff $\bar{w}_t$. We refer to Δ_t as the "wealth-accumulation wedge."

Define x_{it} as the *log* of wealth w_{it}, scaled by the accumulated economic growth g_t over time. We work with x_{it} when simulating the model to generate the wealth distribution. The stochastic law of motion for x_{it} follows

$$dx_{it} = (ye^{-x_{it}} - \rho + r_t^m - g_t + \mathbf{1}\{x_{it} \geq \bar{x}_t\}\Delta_t - \tfrac{1}{2}\sigma^2)dt + \sigma dZ_{it}, \tag{2}$$

where $\bar{x}_t$ is the log scaled transform of the wealth access cutoff $\bar{w}_t$. This law of motion results in a *stationary* distribution of x on the real line, so we do not need to move our grid for x over time when conducting simulations of wealth accumulation.

Ultimately, the wealth distribution is governed by three forces. First, the base rate of return on wealth net of economic growth—the familiar "$r - g$" term, $r_t^m - g_t$—determines the overall tendency

[13] A vast literature shows that variation in labor income does not help explain wealth inequality in the data, especially regarding the concentration of wealth at the very top. See Benhabib and Bisin (2018) for a review.

[14] See Wachter (2013) for the analytical derivation.

of wealth to concentrate. Second, the wealth-accumulation wedge, Δ_t, together with access as summarized by $\bar{x}_t$, governs how strongly innovation-driven returns accrue to high-wealth individuals. Third, preference and risk parameters, namely the time discount rate ρ and idiosyncratic return volatility σ, shape both the level and the dynamics of inequality.

In particular, σ acts as a diffusion force that counteracts the concentration generated by Δ_t: by inducing mobility across the wealth distribution, including across the access cutoff $\bar{w}_t$, it spreads innovation rents beyond the top. Higher idiosyncratic volatility therefore dampens the inequality effects of the wealth-accumulation wedge.

In the following section, we describe how we calibrate and estimate these forces using the data.

4 Calibration and Estimation

Return heterogeneity in our model of wealth accumulation arises because the wealthy have exclusive access to the innovation rents created by private firms. Our goal is to explain the increase in wealth inequality in recent decades, with a particular focus on the top 1% share of wealth. As a natural first step, we assume that the access cutoff, $\bar{w}_t$, is set such that only individuals in the top 1% of the wealth distribution have access to private innovation rents. Under this assumption, the trend in the wealth-accumulation wedge, Δ_t, between individuals in the top 1% and the rest is governed by three factors: the dynamics of corporate innovation rents (shown in Figure III), the dynamics of the private innovation share (e_t in Figure IV), and (because Δ_t is expressed in after-tax terms) the dynamics of the marginal tax rate on long-term capital gains (τ_t^p in Figure VIII).

Formally, denote by V_t capitalized corporate innovation quasi-rents, measured as the aggregate value of corporate patents in year t net of R&D expenses incurred in year t (that is, the year-by-year difference between the two red lines in Panels (a) and (b) of Figure III). Similarly, denote by V_t^l and V_t^u the capitalized innovation rents created by stock market listed (public) and unlisted (private) firms in year t, respectively. By definition, V_t^l and V_t^u are related to V_t by:

$$V_t^l = (1 - e_t) \cdot V_t,$$

$$V_t^u = e_t \cdot V_t.$$

In what follows, we explain how we incorporate data on the time-varying private innovation share e_t and corporate innovation rents V_t into the simulation of wealth dynamics.

The top 1% have access to both public and private firms and thus share in all corporate innovation rents, $V = V^l + V^u$. Our maintained assumption for now is that the other 99% can only invest in public firms and thus share only in V^l. We assume homogeneity in splitting public-firm innovation rents, such that all individuals in the economy share in V^l in proportion to their wealth.[15] We similarly assume homogeneity within the top 1%, such that individuals in the top 1% share in V^u in proportion to their wealth. As a result, the wealth accumulation rate is the same for all individuals within (but not across) the two groups, which we specify next.

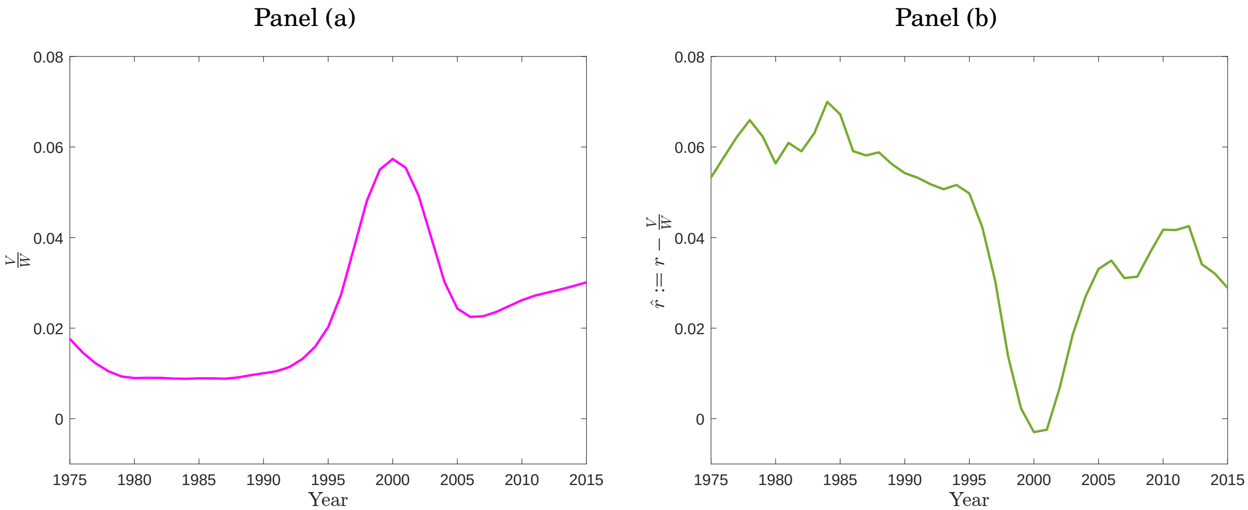
The pre-tax rate of return on wealth in the economy, r, consists of two components: one that is related to corporate innovation rents, and another (denoted $\hat{r}_t$) that captures all other sources of capital income. Recall from Section 2.2 that Kogan et al. (2017) measure the value of a patent based on the market-adjusted change in a firm's stock market value when the patent office approves the firm's patent application. Ignoring returns from other sources of capital income ($\hat{r}_t$), the value of the representative investor's wealth in year t increases by their share in the aggregate Kogan et al. value of corporate patents granted that year. At the same time, their wealth decreases by their share in that year's corporate R&D expenses (which fund the development of future patentable inventions). Since V_t is defined as the difference between the value of patents granted in year t and R&D expenses incurred in year t, we have that V_t/W_t captures the percent change in aggregate wealth due to corporate innovation rents. We refer to V_t/W_t as the "innovation wealth change."

By definition, the pre-tax rate of return on wealth in the economy, r_t, equals $\frac{V_t}{W_t} + \hat{r}_t$. Figure IX decomposes r_t into these two components: the innovation wealth change, $\frac{V_t}{W_t}$, in Panel (a), and the wealth change from all other sources of capital income, $\hat{r}_t = r_t - \frac{V_t}{W_t}$, in Panel (b). On average, $\frac{V}{W}$ equals 2.25% in our sample period, or roughly one-third of the aggregate return on wealth. This may seem large at first glance, but it is squarely in the range implied by standard endogenous-growth models of technological change.[16]

[15] In other words, we are assuming that the top 1% do *not* substitute investments in private firms for investments in public firms. This assumption is conservative to the extent that substitution would amplify the wealth-accumulation wedge Δ_t, leading to a larger rise in the top 1% wealth share.

[16] For example, in Romer (1990), the steady-state value of newly created technologies satisfies $\dot{A}P_A = g\frac{\alpha+\beta}{r}(1-\alpha-\beta)Y$.

Figure IX: Disaggregating the aggregate pre-tax return on wealth



Note: Panel (a) plots V_t/W_t, the percent change in aggregate wealth due to corporate innovation rents. V_t is the aggregate imputed value of all U.S. patents granted to U.S. firms net of R&D spending, as plotted in Figure III. W_t is net aggregate private wealth (i.e., financial and non-financial assets net of financial liabilities). We use a 10-year moving average to smooth the data. Panel (b) plots $\hat{r}_t = r_t - V_t/W_t$, the aggregate return on wealth from all sources of capital income other than corporate innovation rents.

Disaggregating r into $\hat{r}$ and V/W, we can write the post-tax return on wealth for the top 1% and for the other 99% as

$$\textbf{Top 1\%:} \quad r_t^m + \Delta_t = (1-\hat{\tau}_t)\hat{r}_t + (1-\tau_t^p)\left(\frac{V_t^l}{W_t} + \frac{V_t^u}{W_t^{top}}\right),$$

$$\textbf{Bottom 99\%:} \quad r_t^m = (1-\hat{\tau}_t)\hat{r}_t + (1-\tau_t^p)\frac{V_t^l}{W_t},$$

where W_t is aggregate wealth and W_t^{top} is the wealth of individuals in the top 1%. Recall that we assume that wealth changes due to corporate innovation rents constitute long-term capital gains and so are taxed at the marginal long-term capital gains tax rate τ^p. Returns from all other sources of capital income, $\hat{r}$, are taxed at the weighted-average tax rate $\hat{\tau}$, which differs from τ introduced in Section 2.5.2 only because the weights need adjusting for the fact that we decompose total capital income into two components: $\hat{r}$ and V/W.[17]

Using the definitions of V^u and V^l, we can rewrite the post-tax return on wealth for the top 1%

Using a capital share of 1/3, output growth of 3%, and a rental rate of 6.66% implies $\dot{A}P_A \approx 0.1Y$. Interpreting this as aggregate innovation rents V and using $W/Y = 5$ yields $V/W \approx 0.02$.

[17] If $\tau^p = \hat{\tau} = \tau$, we can verify that $r_t^m(W_t - W_t^{top}) + (r_t^m + \Delta_t)W_t^{top} = (1-\tau_t)r_tW_t$, i.e., the average post-tax return on aggregate wealth in the economy is $(1-\tau_t)r_t$, as expected.

and for the other 99% as a function of the private innovation share (e_t) and the innovation wealth change (V_t/W_t):

$$\textbf{Top 1\%:}\quad r_t^m + \Delta_t = r_t^{ave} + \ (1-\tau_t^p)\ e_t\ \frac{V_t}{W_t}\ (\frac{1}{s_t^{top}} - 1), \tag{3}$$

$$\textbf{Bottom 99\%:}\quad r_t^m = r_t^{ave} - \ (1-\tau_t^p)\ e_t\ \frac{V_t}{W_t}, \tag{4}$$

where

$$r_t^{ave} = (1-\hat{\tau}_t)\hat{r}_t + (1-\tau_t^p)\frac{V_t}{W_t} = (1-\tau_t)r_t \tag{5}$$

is the average after-tax return on aggregate wealth in the economy, and $s_t^{top} = W_t^{top}/W_t$ is the wealth share of the top 1%.

Owing to their exclusive access to private innovation rents, the top 1% will accumulate wealth at a higher rate given by the wealth-accumulation wedge, Δ_t:

$$\Delta_t = (1-\tau_t^p)\ e_t\ \frac{V_t}{W_t}\ \frac{1}{s_t^{top}}. \tag{6}$$

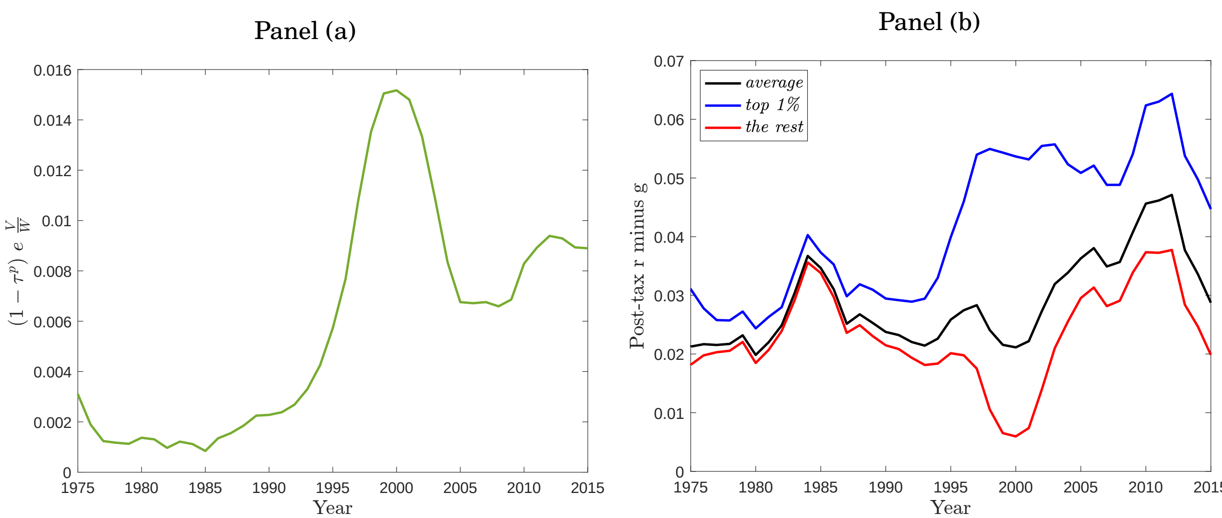
In our model, Δ_t governs the dynamics of wealth inequality, and in particular the top 1% wealth share. As equation (6) makes clear, Δ_t has four determinants: it is decreasing in the tax on long-term capital gains (τ_t^p), increasing in the private innovation share (e_t) and in the innovation wealth change ($\frac{V_t}{W_t}$), and decreasing in the top 1% wealth share (s_t^{top}).[18]

Figure X, Panel (a) plots the term $(1-\tau_t^p)\ e_t\ \frac{V_t}{W_t}$, the after-tax percent change in aggregate wealth that is due to private innovation rents—the private innovation wealth change for short. It is this term that is the source of the wealth-accumulation wedge Δ_t, as derived in equation (6). The figure shows that the private innovation wealth change has risen since the 1990s, to values of around 1 percentage point a year.

Figure X, Panel (b) uses the rates of returns on wealth derived in equations (3) to (5) to plot the "r minus g" term that is at the heart of existing models of wealth inequality dynamics, alongside the time series of our measures of the returns earned by the top 1%, $r_t^m + \Delta_t$, and by the other 99%, r_t^m

[18]The last comparative static follows because at higher s_t^{top}, the private innovation wealth change, $e_t \cdot \frac{V_t}{W_t}$, is shared among individuals with greater wealth, which reduces the rate of wealth accumulation for each of them.

Figure X: Heterogeneous returns on wealth



Note: Panel (a) plots the after-tax return on wealth that is derived from exclusive access to private innovation rents, $(1-\tau^p)\ e\ \frac{V}{W}$, which is the source of the wealth-accumulation wedge Δ_t between the top 1% and the rest. Panel (b) plots the estimated rates of return for the top 1% of the wealth distribution and for the other 99%, as well as the average rate of return in the economy net of the economic growth rate g_t. Returns are estimated from equations (3) to (5) using data on s_t^{top}, r_t, $\frac{V_t}{W_t}$, e_t, τ_t, and τ_t^p. Data on g_t are constructed from real GDP per capita from the Penn World Table and smoothed using a 20-year moving average (as in Gabaix et al., 2016).

(net of economic growth g_t). Over the period from 1975 to 2015, "r minus g" ranges between 2.1% and 4.8%, with an upward trend over time. The series for the top 1% is consistently above the "r minus g" line while the series for the bottom 99% is consistently lower. The returns of the top 1% have trended upward, from 2.8% in 1979 to 4.5% in 2015. We see no comparable upward trend for the bottom 99% over the post-1979 period. The divergence reflects the fact that the top 1% have increasingly earned "exclusive returns" as both the value of corporate innovation and the share of corporate innovation that is generated by private firms have increased over time.

Estimating ρ and calibrating σ. Since our goal is to explain the *rise* in wealth inequality in recent decades, a natural initial steady state is 1979, the year in which wealth inequality began to increase (see Figure II). We estimate the time discount rate ρ by matching the top 1% wealth share in the steady state of the model to its empirical counterpart in 1979.

We obtain the steady-state distribution of wealth in three steps. First, we construct r^m and Δ as of 1979 using equations (3) to (5) and data on the (pre-tax) return on capital r_t, the innovation wealth change V_t/W_t, the private innovation share e_t, tax rates τ_t and τ_t^p, and the top 1% wealth share s_t^{top}.

Second, we simulate the dynamics of log-scaled wealth x_{it} in equation (2) forward until convergence. The initial distribution is the steady state of the benchmark model without exclusive access ($e = 0$), for which Gabaix et al. (2016) provide a unique analytical solution. Third, at each iteration, we update the access cutoff $\bar{x}_t$ using the *lagged* simulated distribution. The limiting distribution defines the steady state with exclusive access.

We estimate ρ by iterating over candidate values until the model-implied top 1% wealth share in steady state matches the data in 1979. In the model with exclusive access to private innovation rents, this yields $\rho = 0.052$, corresponding to a discount factor of $1/(1+0.052) \approx 0.95$, a standard value in the macroeconomics literature. In the benchmark model without exclusive access ($e = 0$), the estimate is slightly lower, at $\rho \approx 0.049$.[19]

Starting from these two steady-state distributions, we simulate the *dynamics* of the wealth distribution from 1979 onward. At each date t, we feed into equation (2) the time-varying objects r_t^m and Δ_t, constructed from data on r_t^{ave}, τ_t^p, V_t/W_t, and the lagged simulated wealth distribution (used to measure s_t^{top}). The access cutoff $\bar{x}_t$ is likewise updated using the lagged distribution.

Simulating the wealth distribution also requires a value for the idiosyncratic return volatility σ. Direct measurement of σ is challenging, as it requires detailed micro data on household balance sheets. Bach, Calvet, and Sodini (2020) report values as high as 25% for wealthy Swedish households, while Fagereng et al. (2020) find values in the range of 10–20% for Norwegian households. Gabaix et al. (2016) calibrate σ to 30%, which they note is at the upper end of estimates in the U.S. context. We adopt this conservative value of $\sigma = 0.3$ and assess robustness to alternative calibrations in Section 6.[20]

In conclusion, our procedure ensures that the model's dynamics are driven by the observed evolution of scaled innovation rents V_t/W_t and their private share e_t, rather than by time variation in preference or risk parameters.

[19] The benchmark model generates a lower top 1% wealth share for a given ρ. Matching the 1979 target therefore requires a lower ρ, which increases wealth concentration in steady state.

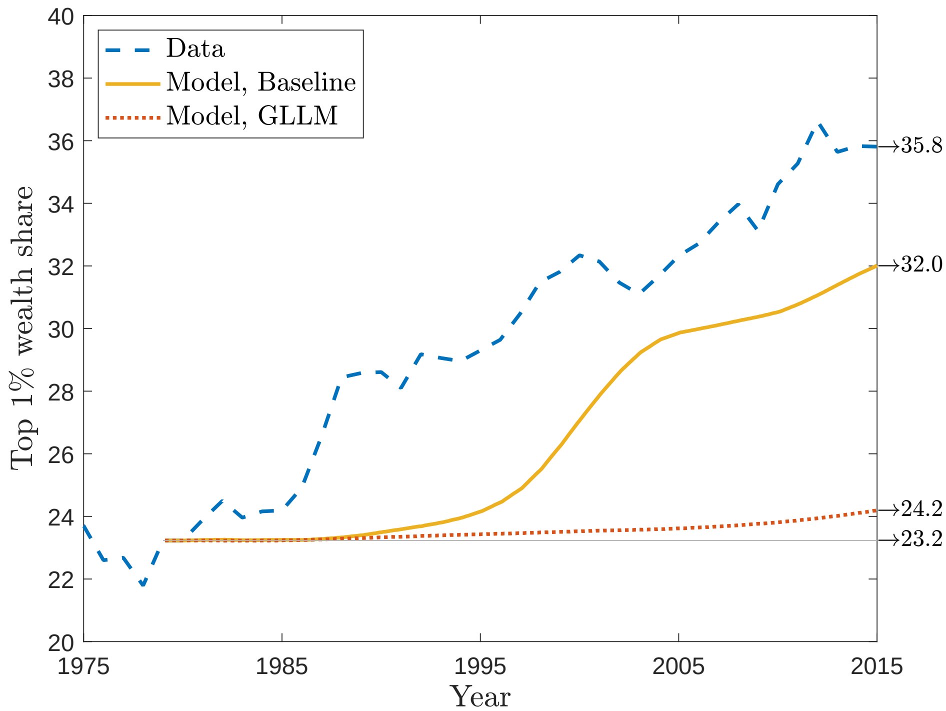
[20] As we will show, a higher σ is conservative in our framework because it increases mobility across the wealth distribution and attenuates the impact of exclusive access to private innovation rents on wealth inequality.

5 Results

5.1 Baseline Findings

In this section, we present our main results on the dynamics of wealth inequality when the top 1% have exclusive access to private innovation rents. Figure XI shows the top 1% wealth share in the data alongside the simulated dynamics from our model. For comparison, the figure also includes simulation results from the basic model of Gabaix et al. (2016) without exclusive access (GLLM).

Figure XI: Dynamics of wealth inequality



Note: The figure shows the evolution of the top 1% wealth share in the data and in two simulation models: our baseline, featuring exclusive access to private innovation rents; and another without exclusive access, as presented in Gabaix et al. (2016). The two models are separately estimated to match the top 1% wealth share in 1979 by their respective steady states; they are calibrated with data for the wealth accumulation rate from 1979 to 2015.

We find that exclusive access to private innovation rents can account for a large share of the increase in wealth inequality. Figure XI shows that, in the data, the top 1% wealth share rises by 12.6 percentage points (from 23.2% to 35.8%) between 1979 and 2015. The model with exclusive access predicts an increase of 8.8 percentage points (from 23.2% to 32.0%) over the same period. Thus, the widening wealth-accumulation wedge (between the top 1% and the rest) shown in Figure X, Panel

(a) can explain as much as 70% of the observed increase in the top wealth share.[21]

Importantly, Figure XI shows that the basic model without exclusive access (GLLM) fails to generate a rise in wealth inequality: the predicted increase is just 1 percentage point (from 23.2% to 24.2%). The GLLM model relies solely on movements in the average post-tax return on capital net of economic growth, "r minus g." However, from the late 1970s to the mid-2010s, "r minus g" does not rise much (see Figure X, Panel b). First, while the pre-tax return is relatively stable from the 1970s to the 1990s, it falls after 2000 (see Figure VI). Second, our tax calculations reflect that interest income is only a small share of capital income for the wealthy: capital gains and dividends dominate, and their tax rates do *not* fall much between the 1970s and the 2010s (see Figure VIII). As a result, "r minus g" does not increase significantly on a *post-tax* basis. Consequently, the implied rise in the top wealth share in the GLLM simulation is minimal.

The divergence between the two models underscores the important role of exclusive access to private innovation rents in shaping the wealth distribution. While a model with uniform returns fails to reproduce the observed dynamics of inequality, incorporating exclusive access substantially improves explanatory power. This highlights the importance of heterogeneity in access across the wealth distribution, rather than an overall rise in the return to capital.

5.2 Counterfactual Analyses

5.2.1 Private Innovation Wealth Change

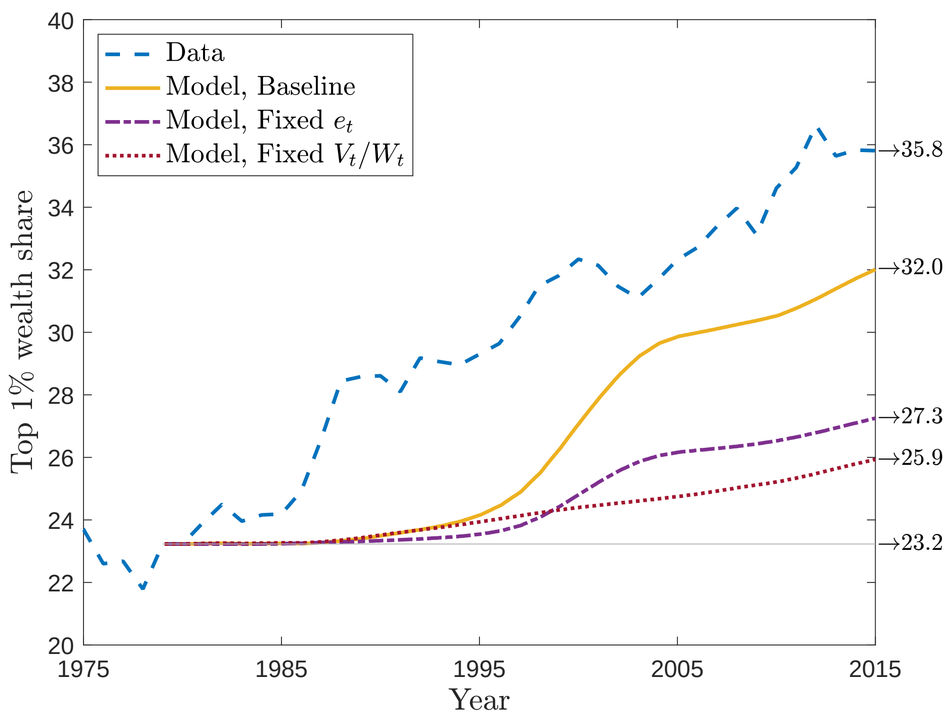
Given exclusive access, the wealth-accumulation wedge between the top 1% and the rest, Δ_t, depends on two factors: 1) the percent change in aggregate wealth due to corporate innovation rents, V_t/W_t, and 2) private firms' share of innovation rents, e_t. In this section, we first show that increases in both V/W and e contribute to the simulated rise in wealth inequality documented in Section 5.1 and then quantify their relative contribution. To do so, we run counterfactual analyses that separately change V/W and e from the observed values in the data.

Figure XII graphs the simulated dynamics of the top 1% wealth share under two scenarios: one that holds the wealth change due to innovation, V_t/W_t, fixed at its initial 1979 value and lets the

[21] Recall that both the increase in aggregate wealth due to corporate innovation, V_t/W_t, and the increase in the private innovation share, e_t, contribute to the wealth-accumulation wedge; see equation (6). In Section 5.2, we show that each plays a nontrivial role in explaining the rise in the top wealth share.

private innovation share e_t vary as per the data, and another that holds e_t fixed at its initial 1979 value and lets V_t/W_t vary as per the data. The figure shows that both V_t/W_t and e_t have a sizable impact on the top 1% wealth share. Specifically, with e_t held constant, the upward trend in V_t/W_t seen in Figure X would on its own raise the top 1% wealth share by 4.1 percentage points (from 23.2% to 27.3%), while the increase in e_t seen in Figure IV would on its own raise the top 1% wealth share by 2.7 percentage points (from 23.2% to 25.9%).

Figure XII: Counterfactual analyses of the wealth-accumulation wedge



Note: The figure shows the evolution of the top 1% wealth share in the data, in our baseline model, and in counterfactual analyses of the wealth-accumulation wedge. Each model is estimated to match its steady-state top 1% wealth share with data in 1979. The counterfactual analyses hold either the private innovation share (e_t) or the innovation wealth change (V_t/W_t) fixed at its initial 1979 value.

The counterfactuals shown in Figure XII imply that the combined effect of increases in V_t/W_t and in e_t is greater than each increase's individual effect. In isolation, changes in V_t/W_t and e_t give rise to a $4.1+2.7=6.8$ percentage-point increase in the top 1% wealth share. This is smaller than the 8.8 percentage-point increase in our baseline simulation, which combines changes in V_t/W_t and e_t. The difference of 2 percentage points reflects complementarity in the effects of V_t/W_t and e_t: a given increase in corporate innovation rents V_t has a larger effect on wealth inequality the higher the private-firm innovation share e_t; and a given increase in e_t has a larger effect on wealth inequality the more valuable is corporate innovation. The empirical fact that both V_t/W_t and e_t have been trending up over the 1979-2015 period means that both trends reinforce each other, resulting in a larger increase in the top 1% wealth share.

5.2.2 The Exclusive Access Criterion

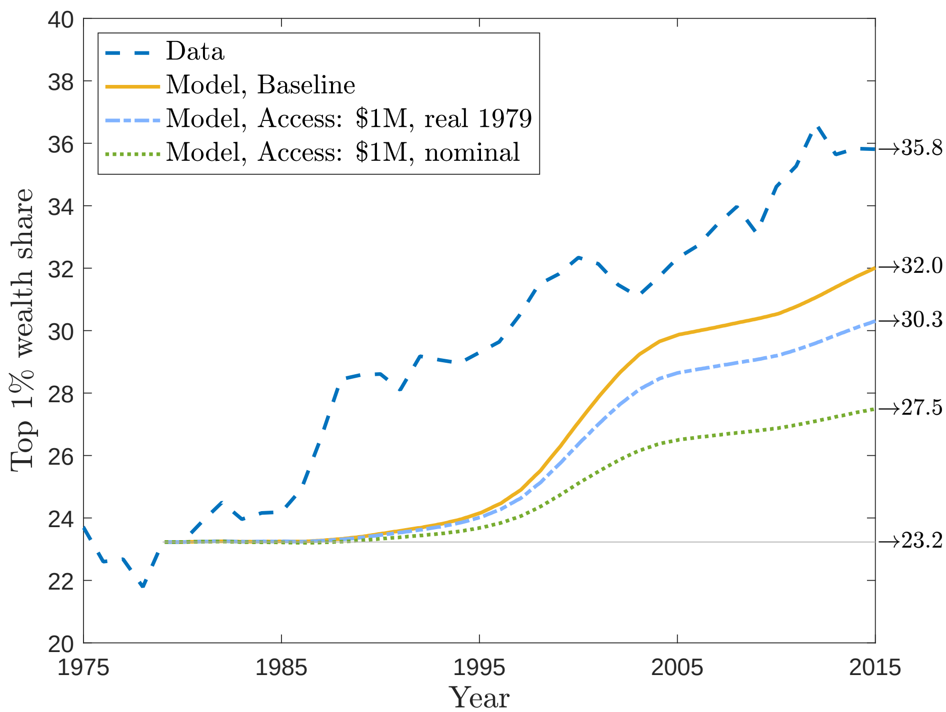
Our baseline simulation assumes that access to private innovation wealth creation, e_tV_t/W_t, is restricted to the top 1% in every year. This assumption can be motivated based on the empirical fact that the concentration of private-business equity is remarkably constant over time (see Figure V). In other words, in the data, it is not the case that individuals in the lower wealth percentiles increase their share of private-business equity over the sample period. In this section, we consider alternative access criteria that expand, over time, the set of individuals with access to private innovation wealth creation. As a result, wealth should become less concentrated at the top.

We consider two counterfactual analyses. The first captures the fact that the SEC's "accredited-investor" rules are based on a *nominal* threshold (here: \$1 million in net worth not including the primary residence). This threshold roughly corresponds to the minimum wealth of the top 1% in 1979 (same as in our baseline model), but over time, asset inflation will naturally expand the set of accredited investors beyond the top 1%.

The second counterfactual analysis considers the possibility that investment in private firms requires a fixed cost (perhaps a search cost) whose size increases with inflation but not with wealth. We implement this counterfactual by restricting access to private innovation rents to those individuals whose wealth in a given year exceeds the minimum wealth in 1979's top 1% cohort (about \$1 million) in *real* terms.

Figure XIII reports the two counterfactual simulations and compares them to the data and to the baseline model. As expected, wealth becomes less concentrated at the top when a broader set of individuals (beyond the top 1%) gain access to private innovation rents over time. In particular, the top 1% wealth share increases from 23.2% in 1979 to 27.5% in 2015 under the accredited-investor scenario of a nominal wealth cutoff—less than the increase to 32.0% in the baseline. This implies that the SEC's accredited-investor rules are *not* the binding constraint on access to private innovation rents and so cannot explain the rise in wealth inequality.

Figure XIII: Counterfactual analyses of the access criteria



Note: The figure shows the evolution of the top 1% wealth share in the data, in our baseline model, and in counterfactual analyses of the access criteria. Each model is estimated to match its steady-state top 1% wealth share with data in 1979. In the baseline model, access to private innovation rents is restricted to the top 1% in a given year. The counterfactual analyses instead restrict access to those individuals whose wealth in a given year exceeds the minimum wealth in 1979's top 1% cohort (about $1 million), either in nominal or in real terms.

Restricting access based on a real wealth cutoff of $1 million in 1979 dollars comes closer to the baseline increase: the top 1% wealth share increases from 23.2% in 1979 to 30.3% in 2015 in this counterfactual. The shortfall compared to the baseline increase to 32.0% suggests that frictions that keep access tied to the *relative* wealth in the cross-section—rather than absolute wealth levels—play a key role in explaining the rise in wealth inequality over time.

5.3 Policy Experiment: Taxes and Subsidies

We study four tax-policy counterfactuals to assess how taxation interacts with innovation-driven wealth accumulation. Figure VIII in Section 2.5.2 summarizes the evolution of U.S. taxes on interest income, dividends, and long-term capital gains since 1979.

Capital gains taxation. Capital gains taxes declined substantially over the period, with the statutory rate τ_t^p falling from 26.5% in 1979 to a low of 15% in 2006–2012. Holding τ_t^p fixed at its 1979

Table I: Counterfactual tax policies

	Baseline	fixed τ^p at 1979 value	fixed τ^i & τ^d at 1979 value	$\downarrow \tau^p$ to 0 for top 1%, by 2015	remove 10% R&D subsidy
	(1)	(2)	(3)	(4)	(5)
Top 1% wealth share (%), 1979	23.2	23.2	23.2	23.2	23.2
Top 1% wealth share (%), 2015	32.0	30.8	30.7	34.6	31.0
Change (percentage points)	8.8	7.6	7.5	11.4	7.8

Note: The table reports the predicted rise in our baseline simulation and in counterfactual scenarios of the tax rate on alternative sources of capital income (τ_t^i, τ_t^d, and τ_t^p) and the subsidy on R&D expenses in the data.

level reduces the increase in the top 1% wealth share from 8.8 percentage points in the baseline to 7.6 percentage points (Table I, column (2)), indicating a meaningful contribution of capital gains tax reductions to rising wealth inequality.

Taxes on interest income and dividends. In a second counterfactual, we hold the tax rates on interest income and dividends, τ_t^i and τ_t^d, fixed at their 1979 levels. Despite much larger declines in these rates in the data, this counterfactual yields a reduction in top wealth accumulation no greater than in the first counterfactual: the top 1% share rises by 7.5 percentage points (Table I, column (3)). The reason is that capital gains taxes directly govern the wealth-accumulation wedge at the top, and long-term capital gains account for an increasing share of capital income (Figure VII).

Zero effective capital gains taxation at the top. We next consider a polar counterfactual motivated by the "buy–borrow–die" mechanism, under which the effective capital gains tax rate for the top 1% declines linearly to zero by 2015 (Fox and Liscow, 2025). Under this scenario, the top 1% wealth share rises by 11.4 percentage points, reaching 34.6% in 2015—close to the observed value of 35.8% (Table I, column (4)). This experiment shows that exclusive access to private innovation rents combined with very low effective capital gains taxation can account for nearly the entire rise in top wealth concentration.

R&D tax credits. Finally, we evaluate the distributional effects of R&D tax credits, which average about 10% since the introduction of the federal research credit in 1981 (Hall and Van Reenen, 2000). Eliminating the subsidy and assuming a one-for-one reduction in capitalized innovation rents lowers the increase in the top 1% wealth share to 7.8 percentage points (Table I, column (5)). In the model, R&D tax incentives therefore contribute to rising wealth inequality by amplifying innovation-driven wealth accumulation at the top.

6 Robustness

We consider four key key sets of robustness tests to the baseline analysis presented in Section 5 and assess their implications for explaining the rise in wealth inequality. These tests examine the sensitivity of our results to the modeling of the right tail of the wealth distribution, to assumptions about access to private innovation rents, and to potential measurement concerns in the underlying data. By way of preview, we find that, across these alternative specifications, exclusive access to private innovation rents can explain at least *half* of the observed rise in top wealth shares from 1979 to 2015.

6.1 The Idiosyncratic Return on Wealth

The idiosyncratic return on wealth, controlled by the parameter σ in equation (1), affects the extent to which Δ_t, the wealth-accumulation wedge between those at the top of the wealth distribution and the rest, leads to rising wealth inequality over time. Larger idiosyncratic shocks to wealth σ generate more mobility into and out of the top 1%. Thus, when σ is larger, the private innovation rents to which individuals in the top 1% have access will leak to lower percentiles over time, resulting in a *smaller* predicted rise in the top 1% wealth share.[22]

In this section, we consider the robustness of our findings to alternative choices of σ. Recall that our baseline calibration sets $\sigma = 0.3$, which, as discussed in Section 4, is at the upper end of estimates reported in the literature and so is conservative. Here, we consider two alternative choices: $\sigma = 0.2$ (which corresponds to empirical estimates for Swedish and Norwegian households) and an extreme case of $\sigma = 0.4$.[23]

Table II summarizes our findings. The table reports the top 1% wealth shares in 1979 and in 2015 and the change between 1979 and 2015. Column (1) shows the realizations from the data while column (2) shows our baseline estimates. Columns (3) and (4) report results for $\sigma = 0.2$ and $\sigma = 0.4$,

[22] In the basic model without exclusive access (GLLM), the change in the predicted rise goes in the opposite direction. In the GLLM model, idiosyncratic shocks to wealth σ and a rising "r minus g" are the only source of wealth inequality. Greater dispersion in returns as σ increases then leads to a *larger* rise in the top wealth share over time.

[23] Given a new σ, we re-estimate the parameter ρ of our model with exclusive access to private innovation rents by re-matching the steady state of the model in 1979. We then re-simulate the economy over time.

respectively. Our results are sensitive to the choice of σ in the expected direction. The lower $\sigma = 0.2$ calibration generates a larger rise in the top 1% wealth share of 10.4 percentage points between 1979 and 2015 (compared to the 8.8 percentage-point baseline estimate). This confirms that our baseline estimates are conservative.

Even with an extremely (and arguably implausibly) high value of $\sigma = 0.4$, our model of exclusive access to private innovation rents predicts a substantial rise in the top 1% wealth share of 7.2 percentage points—only marginally smaller than the baseline estimate of 8.8 percentage points and still large in relation to the realized rise of 12.6 percentage points in the data.

Table II: Robustness tests: σ and $\bar{w}_t$

	Data	Model				
		Baseline	$\sigma = 0.2$	$\sigma = 0.4$	Access for top 5%	Access for top 10%
	(1)	(2)	(3)	(4)	(5)	(6)
Top 1% wealth share (%), 1979	23.2	23.2	23.2	23.2	23.2	23.2
Top 1% wealth share (%), 2015	35.8	32.0	33.6	30.4	30.2	29.6
Change (percentage points)	12.6	8.8	10.4	7.2	7.0	6.4

Note: The table reports the realized rise from 1979 to 2015 in the top wealth share in the data (column 1) along with the predicted rise in our baseline simulation (column 2) and in alternative specifications that vary the parameters for idiosyncratic shocks to wealth, σ, and for who has access to private innovation rents, $\bar{w}_t$. In the baseline model, σ is calibrated to 0.3, and access is restricted to individuals in the top 1%.

Taken together, these results show that our mechanism does not rely on a knife-edge parameterization of the right tail of the wealth distribution. Economically meaningful perturbations to the idiosyncratic return parameter σ—which governs mobility into and out of the top—leave the quantitative implications largely intact. In other words, the rise in wealth concentration is not driven by a particular choice of tail thickness or persistence.

Moreover, in conjunction with our counterfactual analyses, these findings indicate that the model's explanatory power is tied to the observed evolution of innovation dynamics—specifically, the rise in innovation rents and their increasing concentration in private firms—rather than to parameter tuning. The data-driven changes in V_t/W_t and e_t are the central drivers of the model's results.

6.2 Broader Access to Private Innovation Rents

Our baseline model sets $\bar{w}_t$ such that access to private innovation rents is restricted to individuals in the top 1% of the wealth distribution. Data on who invests in the private firms that create innovation rents are not available for the U.S., but we can view the SCF data on private-business equity in Figure V as a lower bound. The reason is that private-business equity among the less well off more likely represents self-employment (e.g., plumbers or medical practices) than investments in risky innovative private firms (investment in which is restricted by the SEC's accredited-investor rules). Naturally, broadening the access criterion beyond the top 1% dilutes the top 1%'s wealth-accumulation wedge, Δ_t, which in turn will reduce the predicted rise in the top 1% wealth share. The empirical question is, by how much?

In this section, we consider the robustness of our findings to alternative access assumptions. Specifically, we broaden access to private innovation rents to individuals in either the top 5% or the top 10%, on the following terms (chosen to match the patterns in Figure V): we assume that individuals in the top 1% have access to all private innovation rents $e_t V_t$ (as in the baseline), that individuals in percentiles 95-99 have access to half of $e_t V_t$, and that individuals in percentiles 90-94 have access to a quarter of $e_t V_t$. We calculate each individual's wealth accumulation rate by distributing aggregate $e_t V_t$ in proportion to the product of the individual's wealth and the calibrated access weight of her wealth percentile. We then re-estimate the model using the steady-state top 1% wealth share outcome in 1979.

Table II, columns (5) and (6) report the results. Whether access is broadened to the top 5% or to the top 10%, our model predicts nearly the same rise in the top 1% wealth share from 1979 to 2015, of 7.0 and 6.4 percentage points, respectively. Consistent with the expected dilution, these estimates are smaller than the baseline estimate of 8.8 percentage points. Still, even when we relax our baseline access criterion, the model can explain at least half of the observed 12.6 percentage-point rise in the top 1% wealth share.

6.3 Within-Top Wealth Inequality

Our model is designed to explain the rise in the concentration of wealth in the right tail of the distribution. To do so, the model focuses on return heterogeneity, which Benhabib and Bisin (2018), Benhabib, Bisin, and Luo (2019), and Hubmer, Krusell, and Smith (2021) show is crucial to understanding the rise in the top wealth share. To keep the analysis tractable, we abstract from earnings heterogeneity and progressive income taxation, which are required to generate realistic outcomes for the rest of the wealth distribution (which is not our focus).

In this section, we narrow our focus to the right tail (for which our assumptions are considered the most appropriate) and model *within-top* wealth inequality, which we measure as the ratio of the wealth of the top 1% to the wealth of the top 10%. We proceed as follows. We first re-estimate the time discount rate in individuals' preferences, ρ, by matching the ratio of the wealth of the top 1% to the wealth of the top 10% in 1979 and then re-simulating wealth accumulation over time. The new estimate of ρ is 0.067.

Table III reports the results for within-top wealth inequality. In the data, the top 1% increase their share of wealth in the top 10% by 13.4 percentage points between 1979 and 2015, from 35.5% to 48.9%. Our baseline model, matched to the top 1% wealth share in 1979, predicts an increase of 10.5 percentage points. The alternative specification, matched to the ratio of the wealth shares of the top 1% and the top 10% in 1979, predicts a 12.8 percentage-point increase.

Table III: Robustness test: Within-top inequality

	Data	Model	
		Baseline	Matching 1979's wealth share ratio
	(1)	(2)	(3)
Top 1% to top 10% wealth share ratio, 1979 (%)	35.5	45.1	35.5
Top 1% to top 10% wealth share ratio, 2015 (%)	48.9	55.6	48.3
Change (percentage points)	13.4	10.5	12.8

Note: The table shows robustness results for the predicted rise in the ratio of the top 1% and the top 10% wealth share. Column (1) shows the values in the data. Column (2) shows the baseline results, in which the model is estimated by matching the top 1% wealth share in 1979. Column (3) shows results for a model that matches the ratio of the top %1 and top 10% wealth shares in 1979.

These results show that our findings are not an artifact of matching only the top 1% wealth share in 1979. Even when we discipline the model using within-top inequality, and thus the shape of the right tail itself, exclusive access to private innovation rents continues to explain nearly the entire rise in concentration within the top between 1979 and 2015.

6.4 Measurement of V_t^u, I_t^u, and e_t

Our analysis relies on measures of innovation rents and R&D expenditures for public and private firms. Two measurement concerns are particularly relevant.

First, our imputation procedure may overstate the value of private-firm patents. Private firms are often estimated to trade at a discount relative to comparable public firms (Koeplin, Sarin, and Shapiro, 2000), which could imply that the value of private-firm patents is overstated in our baseline estimates. To assess this concern, we apply conservative haircuts of 20% to 30% to private-firm patent values and recompute the implied innovation wealth change V_t/W_t and private share e_t.

Second, R&D expenditures of private firms may be underestimated in the NSF data, potentially generating an artificial increase in measured R&D efficiency. To address this concern, we consider a counterfactual in which the ratio of private to public R&D, I_t^u/I_t^l, is held fixed at its 1979 level throughout the sample. This removes the rise in measured private-firm R&D efficiency over time that can be seen in Figure III, Panel B.

Table IV: Robustness tests: Measurement of private innovation rents and R&D

	Data	Model				
		Baseline	20% haircut	30% haircut	Fixed I^u/I^l	Fixed I^u/I^l & 20% haircut
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Top 1% share, (%)						
Top 1% wealth share (%), 1979	23.2	23.2	23.2	23.2	23.2	23.2
Top 1% wealth share (%), 2015	35.8	32.0	30.7	30.1	31.0	29.7
Change (percentage points)	12.6	8.8	7.5	6.9	7.8	6.5

Note: The table shows robustness results for the predicted rise in the top 1% wealth share. Column (1) shows the values in the data. Column (2) reports the baseline model. In columns (3) and (4), we apply haircuts to private firms' imputed patent values of 20% and 30%, respectively. In column (5), we hold the ratio of private to public R&D expenditures, I_t^u/I_t^l, fixed at its 1979 level. Column (6) combines the changes considered in columns (3) and (5). In each case, we recompute the innovation wealth change V_t/W_t and the private share of innovation rents e_t, and then re-simulate the model.

Table IV reports the results. These exercises deliberately bias the measurement against our mechanism. Even so, the model continues to generate a substantial increase in the top 1% wealth share. While the magnitude is somewhat attenuated, the baseline result remains largely intact: even under conservative adjustments to private innovation rents or R&D measurement, the model explains at least half of the observed rise in wealth inequality.

7 Conclusion

Our analysis reveals a previously unmeasured mechanism linking the organization of corporate innovation to the distribution of wealth. Drawing on a long-run series of innovation rents that includes both public and private firms, and documenting the sharp rise in the private-firm share of those rents, we show that access to private innovation rents is both highly concentrated and quantitatively important for the evolution of top wealth shares. Embedding this access channel into a structural model of wealth accumulation allows us to account for much of the observed rise in top wealth concentration since 1979. Importantly, our findings do not rely on a knife-edge parameterization of the upper tail of the wealth distribution, but instead on the observed evolution of innovation quasi-rents and their increasing concentration in private firms.

Our results suggest that changes in where innovation occurs—and who can invest in it—have first-order implications for inequality. More broadly, they highlight the importance of understanding how shifts in the frontier of corporate activity interact with household balance sheets. The growing role of private markets in generating innovation rents raises questions about the allocative, distributional, and policy consequences of innovation occurring outside public capital markets. Future research could explore how access to private-firm equity varies across countries, how innovations financed through private markets diffuse into the broader economy, and how policy interventions could influence the distributional effects of innovation. By tracing return heterogeneity to concrete investment opportunities, our framework opens the door to a richer understanding of how modern innovation ecosystems shape long-run wealth inequality.

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Appendix

A Data

A.1 Aggregate Return on Capital

This section outlines the methodology used to generate the return series presented in Figure VI. The process involves updating and replicating the return series originally provided by Piketty and Zucman (2014) using contemporary data sources. The original series, which was used in Gabaix et al. (2016) for the return on wealth, spans from 1946 to 2010 and is based on a pre-tax rate of return.

The average rate of return on domestic capital is defined as $r_t = \theta_t / \beta_t$, where θ_t represents the capital share and β_t is the wealth-national income ratio. To construct the return series following Piketty and Zucman (2014), we decompose θ_t and β_t into their detailed components and update them using data from the Federal Reserve's Integrated Macroeconomic Accounts (IMA) and the National Income and Product Accounts (NIPA) maintained by the Bureau of Economic Analysis.

Capital share (θ_t): The capital share (θ_t) is defined as total capital income divided by total income. Total income is directly taken from the IMA as nominal national income. Total capital income consists of several components:

- **Corporate capital income**, which includes profits from corporations and is derived from NIPA tables.
- **Housing capital income**, which is the net product of the housing sector and is derived from NIPA tables.
- **Self-employment capital income**, which is the capital income of self-employed individuals and is estimated using data on mixed income derived from NIPA and IMA.
- **Net foreign capital income**, which represents income from foreign investments, adjusted for outflows and inflows, and is sourced from NIPA Table 4.1.
- **Net government interest payments**, which includes interest payments made by the government, net of receipts, and is updated using NIPA Table 3.1.

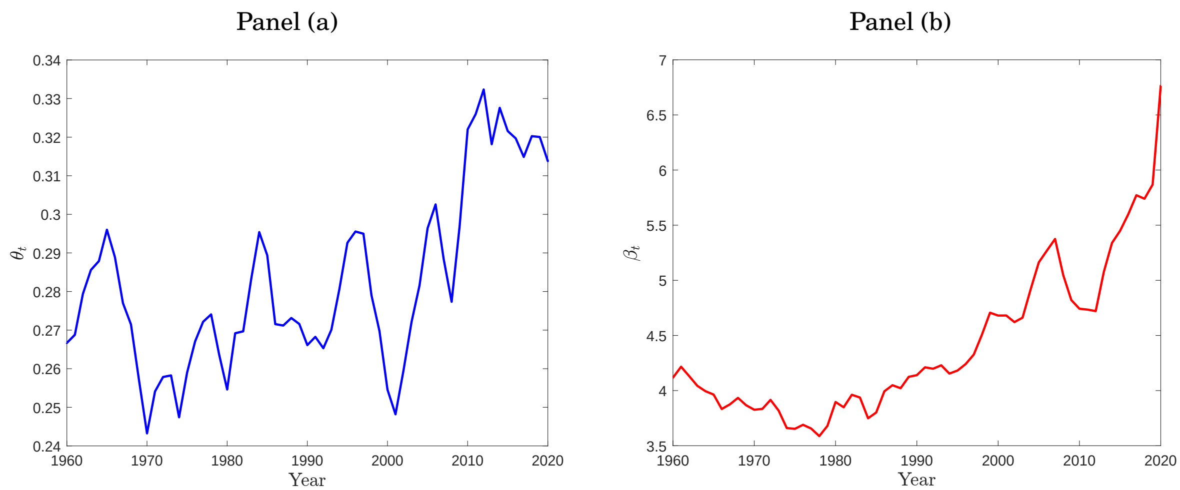
Each of these components is further divided into detailed sub-components, which are updated using the latest available data from NIPA and IMA. Piketty and Zucman (2014) provide the formula for deriving most capital income components using IMA and NIPA as sources. However, in some cases, data from one source has been discontinued. For example, certain series, such as NIPA Table 7.12, are no longer available. We update the corresponding variable using only the remaining data source in such instances. Although the differences are negligible when the series can be derived from both NIPA and IMA, we prioritize the formula based on NIPA data. The IMA-based formula is used only when deriving the series from NIPA is no longer possible. The replicated series for θ_t is presented in Figure A.1, Panel (a).

Wealth-national income ratio (β_t): The wealth-national income ratio (β_t) is defined as net private wealth divided by total income. As with θ_t, total income is taken directly from IMA as nominal national income. Net private wealth is calculated as the sum of financial and non-financial assets, net of financial liabilities. Each of these components is further broken down into detailed sub-components:

- **Financial assets**, which includes assets such as stocks, bonds, and other financial instruments.
- **Non-financial assets**, which includes real estate, durable goods, and other tangible assets.
- **Financial liabilities**, which includes debts such as mortgages, loans, and other liabilities.

Each of these components is updated using the most recent data available from IMA. The replicated series for β_t is presented in Figure A.1, Panel (b).

Figure A.1: Capital share of income and wealth-national income ratio



Note: This graph illustrates the capital share of income (θ_t) (in Panel a) and the wealth-to-national-income ratio (β_t) (in Panel b). The return series is derived from the ratio of these two variables.

A.2 Capital Income Tax

This appendix explains the methodology used to generate the tax-rate series presented in Figure VIII. We construct two time series for tax rates spanning the longest possible periods: one for the marginal tax rate on a composite capital income category, including interest income, dividends, and long-term capital gains, and another for the tax rate explicitly applied to long-term capital gains.

To construct these time series, we rely on the following two series:

- Marginal tax rates on interest income, dividends, and long-term capital gains, presented in Figure A.2, Panel (a).
- Income shares of these components, presented in Figure A.2, Panel (b).

The marginal tax rate on capital income is computed as a weighted average of the marginal tax rates of its components, using the income shares as weights.

Post-1989 data. From 1989 onward, we use the SCF dataset and the NBER TAXSIM model to compute individual-level marginal tax rates. Since we require aggregate tax rates for the top 1% of income earners, we sort households in each year by their adjusted gross income (AGI) and select the top 1%. To compute the aggregate marginal tax rate for a specific income type, we calculate a weighted average of the marginal tax rates for the top 1% of households in each year, using the corresponding income shares derived from SCF as weights. Because SCF data is available only every three years, this procedure provides marginal tax rates for the years 1989 to 2019 at three-year intervals.

Pre-1989 marginal tax rates. Although the SCF has been conducted since 1962, it was not conducted regularly prior to 1989 and the data are not publicly available. As an alternative, we use the report on the NBER TAXSIM website, which presents marginal tax rates for the top 1% of income earners across income types, including interest income, dividends, and long-term capital gains. These series are based on TAXSIM simulations using IRS microdata. The reported series cover 1960–2000, from which we use the pre-1989 estimates.

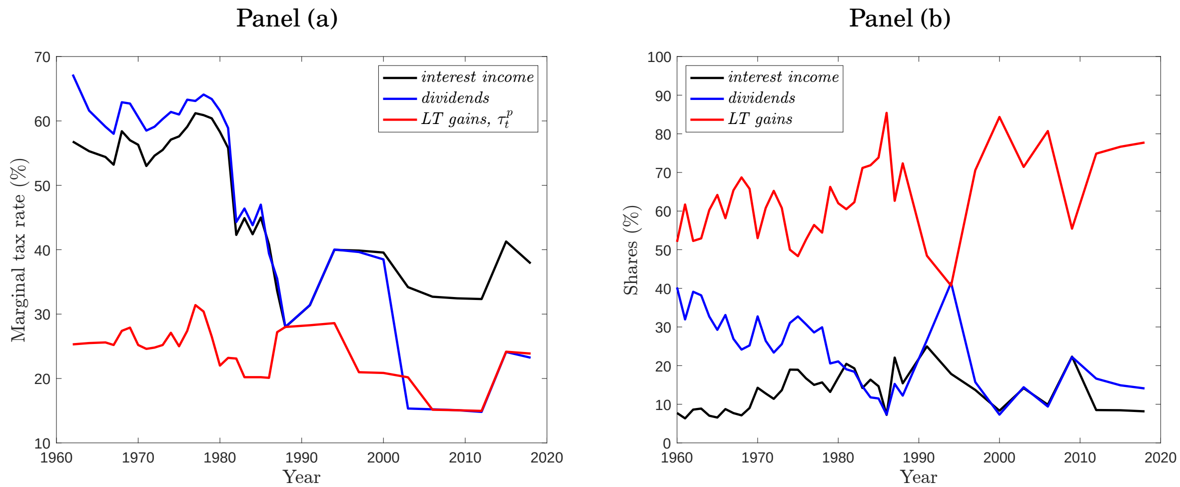
Pre-1989 income shares. The required income shares are obtained from the World Inequality Database (WID), which provides historical data on fiscal capital income components, including:

- Rents
- Interest
- Dividends
- Capital gains
- The capital component of mixed income

Adjustments for long-term capital gains. Since WID does not distinguish between long-term and short-term capital gains, we estimate long-term capital gains shares using historical data from the U.S. Department of the Treasury. We assume a stable 95% share for long-term capital gains in total capital gains, based on available data from 1977 to 1988.

Marginal tax rate for top 1% wealth holders. Following Gabaix et al. (2016), we construct tax series for the top 1% of income earners. Ideally, we would focus on the top 1% of wealth holders, but this is not feasible due to data limitations. Estimating marginal tax rates requires detailed microdata, which are available from the Survey of Consumer Finances (SCF) only from 1989 onward; such data are unavailable for earlier periods. To validate our approach, we compare marginal tax rates for the top 1% of wealth holders and income earners using post-1989 SCF data. Specifically, we rank households by net worth, select the top 1%, and compute marginal tax rates using the same methodology as for the top 1% of income earners. Figure A.3 plots the two series. The difference between the two groups is minimal.

Figure A.2: Marginal tax rates and capital income shares used in calculating the marginal tax rate on capital income



Note: Panel (a) shows marginal tax rates for the components of capital income used in our replication of the overall marginal tax rate. Before 1989, the data come from a report on the TAXSIM website; from 1989 onward, rates are based on our calculations using SCF data. Panel (b) shows the shares of capital income components in total capital income for top 1% income earners, which serve as weights for the overall marginal tax rate. All tax rates and shares are smoothed using 3-year moving averages. Before 1989, the data source is WID, with minor adjustments to long-term capital gains; from 1989 onward, shares are calculated using SCF data.

Figure A.3: Comparison of marginal tax rates on capital income for the top 1% wealth and income

Note: For the red line, we restrict the SCF sample to the top 1% of wealth holders and calculate their marginal tax rates. Similarly, for the blue line, we limit the sample to the top 1% of income earners and perform the same calculation.

A.3 Private Business Equity

We use SCF data to measure aggregate holdings of private business equity (SCF variable 'bus') and total assets ('asset') across the wealth distribution. For 1989 onward, we use waves of the SCF Summary Extract Public Data.[24] For earlier years, we use SCF+ developed by Kuhn, Schularick, and Steins (2020).[25] We report holdings for four groups: the top 1%, percentiles 95–99, percentiles 90–94, and the bottom 90% of the net worth distribution (SCF variable 'networth'). Aggregates are computed using survey weights. Table A.1 reports the results.

Table A.1: Private-business equity across the wealth distribution

	bottom 90%		90-94		95-99		top 1%	
SCF wave	prv-bus	assets	prv-bus	assets	prv-bus	assets	prv-bus	assets
1977	0.2 (3%)	8.6 (41%)	0.3 (5%)	2.6 (12%)	2.7 (45%)	5.6 (27%)	2.8 (47%)	4.3 (20%)
1983	0.5 (10%)	11.1 (38%)	0.7 (12%)	3.4 (12%)	1.6 (29%)	6.2 (21%)	2.8 (50%)	8.4 (29%)
1989	0.7 (10%)	15.3 (38%)	0.7 (9%)	5.0 (13%)	2.1 (27%)	9.1 (23%)	4.1 (54%)	10.9 (27%)
1992	0.7 (10%)	14.7 (39%)	0.5 (8%)	4.6 (12%)	1.9 (27%)	8.6 (23%)	3.8 (55%)	10.1 (27%)
1995	0.6 (8%)	16.1 (38%)	0.4 (5%)	4.8 (11%)	1.2 (16%)	8.1 (19%)	5.1 (70%)	12.8 (31%)
1998	0.8 (9%)	20.2 (37%)	0.5 (6%)	5.9 (11%)	2.0 (21%)	11.7 (22%)	5.8 (64%)	16.1 (30%)
2001	1.2 (10%)	25.1 (36%)	0.8 (7%)	8.3 (12%)	3.0 (25%)	16.6 (24%)	6.7 (57%)	20.5 (29%)
2004	1.3 (10%)	30.0 (37%)	0.8 (6%)	9.3 (11%)	3.1 (23%)	18.1 (22%)	8.3 (62%)	23.9 (29%)
2007	1.2 (6%)	33.4 (35%)	1.0 (5%)	10.0 (11%)	4.8 (26%)	23.5 (25%)	11.5 (62%)	27.9 (29%)
2010	1.2 (8%)	27.7 (33%)	1.0 (7%)	10.8 (13%)	3.4 (23%)	20.2 (24%)	9.0 (62%)	24.5 (29%)
2013	0.9 (6%)	27.1 (32%)	0.8 (5%)	9.8 (12%)	3.8 (26%)	21.2 (25%)	9.4 (63%)	26.3 (31%)
2016	1.2 (6%)	30.8 (29%)	1.2 (6%)	12.6 (12%)	4.8 (23%)	26.2 (25%)	13.7 (66%)	37.0 (35%)
2019	1.3 (6%)	33.1 (30%)	1.1 (5%)	12.5 (11%)	5.3 (24%)	28.6 (26%)	14.0 (65%)	37.1 (33%)

Note: The table reports aggregate holdings of private-business equity and total assets (in trillions of 2019 dollars) for four groups of households: the top 1%, percentiles 95–99, percentiles 90–94, and the bottom 90% of the net worth distribution. Numbers in parentheses show shares of the total across all households, reported separately for private-business equity and total assets. Data come from the SCF Summary Extract Public Data (1989 onward) and SCF+ for earlier years (Kuhn, Schularick, and Steins, 2020).

[24] https://www.federalreserve.gov/econres/scfindex.htm

[25] The corresponding variables in SCF+ are 'ffaass' and 'ffabus' for total assets and private business equity, respectively.