

# Wealth Shares in the Long Run\*

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## Abstract

I decompose the growth of top wealth shares into two terms: (i) an intensive term driven by wealth accumulation by incumbent wealthy households; and (ii) an extensive term driven by the entry of new households. I estimate the relative contribution of these two margins to rising wealth inequality using a novel panel data set of wealth for top wealth households from 1982 to 2018. The extensive margin accounts for roughly half of the rise in wealth inequality at short horizons and over eighty percent over longer horizons. The larger role of entry at long horizons is the result of heterogeneous growth rates among wealthy households. Consistent with my model, this heterogeneity is well captured by a life-cycle effect, wherein newly rich households' wealth growth outpaces that of older households.

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# 1 Introduction

Over the last few decades, there has been a secular rise in top wealth shares. How did a small fraction of households accumulate so much wealth; not just in absolute terms, but relative to the rest of the economy? One explanation is that wealth begets wealth and the rise in wealth inequality is driven by high returns on wealth (Piketty and Goldhammer, 2014; Hubmer, Krusell, and Smith, 2016), resulting in increasing inequality and declining social mobility. Yet there is significant churn in the ranks of the ultra-wealthy. Few households manage to stay on the Forbes list of the 400 richest Americans over long periods of time; only 20 percent of the 1982 Forbes 400 list have family who appear on the list in 2018 (Gomez, 2018; Benhabib, Bisin, and Luo, 2015). Each year, ten percent of Forbes 400 members fall off the list and are replaced by newly wealthy households. In this paper, I study the relative contribution of old and new money to the rise in U.S. wealth inequality.

To isolate these distinct contributions, I present a decomposition of changes in wealth inequality that differentiates between intensive contribution of incumbent wealthy households, whose wealth growth reflects returns on incumbent wealth, and the extensive contribution of new entrants who enter top wealth percentiles by displacing other wealthy households. top wealth percentile absent the effects of entry. The decomposition allows me to quantify the relative importance of these contributions in explaining the secular increase in wealth inequality. When I apply my decomposition to a novel panel of wealthy households, I find that incumbent wealth grows at a rate close to that of aggregate household wealth, meaning that the contribution of the intensive margin is small. Consequently, the displacement term is responsible for over 80 percent of the increase in wealth inequality since 1986.

Understanding the drivers of rising wealth inequality is of clear policy importance. Inequality of realized outcomes can arise from inequality of opportunities, and one role of public policy is to promote equal opportunities and mobility. Many politicians have labeled the rise of wealth inequality as the unjust product of an unfair system and want to directly address wealth inequality through redistributive policies. On the other hand, many of to-

day's Forbes 400 members got there by founding disruptive new firms. Wealth inequality can be celebrated as a sign of a dynamic economy that rewards innovation and entrepreneurship or vilified as a symptom of rent-seeking behavior. My paper helps to distinguish between these competing interpretations by quantifying how much of the rise in top wealth shares is the result of new entrants.

In addition to their implications for wealth inequality, the individual wealth dynamics underlying the increase in wealth inequality are an important quantity in many economic models. In any micro-founded model of consumption and investment behavior, it is agents' beliefs about their consumption and wealth dynamics that drive their decisions. As we typically lack data on agents' wealth, models have been evaluated using aggregate data. Empirical data on household wealth dynamics offer new ways to test existing asset pricing models. Wealthy agents hold a significant fraction of assets and are likely candidates for marginal investors in markets (Malloy, Moskowitz, and Vissing-Jørgensen, 2009). The wealth dynamics of these households are closely linked to the stochastic discount factor and impact asset prices. At a deeper level, differences in growth rates across households inform us about imperfect risk sharing and market frictions. In the presence of such market imperfections, heterogeneity among agents matters for asset prices (Constantinides and Duffie, 1996).

To understand the implications of heterogeneity for wealth inequality and asset prices, I develop an overlapping generations model in which borrowing constraints inhibit some agents' ability to borrow against their future dividend income. Thus, the distribution of wealth matters for the interest rate. I further show that high incumbent returns and wealthy new entrants have starkly different implications for the interest rate, despite both affecting wealth inequality. When wealth inequality increases due to wealthier new entrants, the interest rate falls. This is consistent with the secular decline in interest rates over the recent decades which occurred alongside the rise in wealth inequality.

In the model, measuring the wealth growth of incumbents using repeated cross-sections leads to erroneous conclusions about asset prices. This is because, even in the top percentiles

of the wealth distribution, some agents are not marginal in financial markets. Instead, I propose measuring wealth growth of a fixed population of incumbents. I show that this measurement of cohort wealth growth recovers returns in the economy, even in the presence of borrowing constraints.

In order to measure the returns on incumbent wealth, I construct a panel data set of wealth for ultra-wealthy households. Starting from the time a household first appears on the Forbes 400 list, I track its wealth across multiple hand-collected data sources through to present day. A key challenge in estimating wealth dynamics from existing data sources is that the wealth of the formerly wealthy is unobserved. Without observing the left-tail of wealth dynamics, it is difficult to draw conclusions about expected growth rates. The value of my panel is that it follows each household, irrespective of their present-day wealth. My panel tracks wealth for individuals like Bill Gates and Jeff Bezos, who have stayed on the Forbes 400 list over many years; it also the first panel that tracks wealth estimates for individuals like Richard Adams, who appeared on the list from 1997 to 2000 and peaked at rank 174 with a net worth of \$1.4 billion, only to fall off the list when the tech bubble burst. I provide the first estimates of growth rates of incumbent wealth in the United States at long horizons.

Using my panel data set, I am able to estimate growth rates of wealth by fixing a set of households and calculating their realized wealth growth at long horizons. I estimate growth rates for entry cohorts, comprised of households that entered the Forbes 400 population at the same time. Aggregating at the level of entry cohorts allows me to better estimate average growth rates by averaging over multiple households. At the same time, it allows me to test for differences in average growth rates between cohorts by comparing contemporaneous growth rates between entry cohorts. I also estimate growth rates for incumbent cohorts, comprised of households that appeared on the Forbes 400 list at the same time. Each incumbent cohort consists of multiple entry cohorts, and incumbent growth rates are the wealth-weighted average of entry cohort growth rates. Incumbent growth rates are the appropriate growth

rate for studying changes in wealth shares because they measure the wealth growth of a fixed population of incumbent households, those who were members of the top wealth share at a given point in time. Increases in the top wealth share above and beyond the wealth growth of incumbent top wealth households must be the result of entrants.

The extensive margin accounts for roughly half of the increase in wealth inequality since 2006 and over 80 percent of the increase since 1986. At long horizons, wealthy households have grown at an annual rate of 6.3 percent compared to a growth rate of 5.7 percent for aggregate wealth. Thus, there is evidence in the data to support the view that incumbent wealth self-perpetuates. However, if incumbents were the only driver of increasing wealth inequality, the wealth share of the Forbes 400 would have increased from 0.9 percent of total wealth in 1986 to 1.1 percent in 2018. In reality, the wealth share of the Forbes 400 increased from 0.9 to 2.8 percent over that period.

The increasing role of displacement at longer horizons is the result of heterogeneous growth rates within the incumbent population, as groups with lower growth rates shrink relative to faster growing groups. These effects are difficult to observe in short time-samples. By tracking households that appeared on early Forbes 400 lists, I am able to identify a population of incumbent top wealth households and estimate their wealth growth over long horizons. For the earliest Forbes households, I observe over thirty-five years of wealth estimates. The long period covered by my data set allows me to observe both cross-sectional and time-series heterogeneity in growth rates.

I find that the observed heterogeneity in growth rates is well explained by a life cycle model of wealthy households. Newer entrants to the Forbes 400 list grow at a faster rate than older cohorts of entrants; households also grow at slower rates as they age. Over time, differences in growth rates lead to changes in the composition of wealthy households, so that the instantaneous growth rate overestimates the long-run growth rate of the incumbent wealth share. Ignoring the role of heterogeneous growth rates results in estimates of displacement that are biased downwards and roughly half as large in size.

I find that the secular rise in top wealth shares is primarily the result of displacement. As shown in Figure 1, the wealth held by members of the Forbes 400 has increased from roughly \$100 billion in 1982 to \$3 trillion in 2018. This has significantly outpaced the growth in aggregate household wealth over the same period. However, it has also significantly outpaced the growth in wealth held by those initial Forbes members over the same period. The 1982 Forbes 400 members held \$1 trillion in 2018, while the other \$2 trillion of wealth is the result of displacement.

In the final section of my paper, I examine the implications of my findings for macro-finance models. These models typically have strong predictions for wealth distributions and wealth dynamics but have not been evaluated on their ability to match the data. My estimated wealth dynamics offer a new and important set of empirical moments for model selection. I start with the standard representative agent model and discuss the model's difficulties in reconciling wealth dynamics and asset prices. I show that several extensions to the model are still unable to jointly match my findings. The large role of displacement is strong evidence in support of models of disruptive growth and incomplete markets. The presence of heterogeneous growth rates and life cycle effects in wealth dynamics are consistent with portfolios featuring concentrated ownership in risky firms. Concentrated firm ownership also relates the life cycle effects I observe in wealth growth rates to life cycle effects in firm growth rates. My findings suggest that the underlying drivers of wealth inequality are the same as those underlying other macroeconomic phenomena such as the rise of superstar firms and the fall of the labor share.

## **1.1 Related Literature**

My paper contributes to the growing literature on the rise in top wealth shares (Piketty and Goldhammer, 2014; Kuhn, Schularick, and Steins, 2017; Garbinti, Goupille-Lebret, and Piketty, 2017). This literature focuses on the overall increase in wealth shares, while my paper emphasizes the individual wealth dynamics that underlie the increase in wealth share.

The motivation for focusing on the underlying dynamics is to distinguish between the role of incumbent growth rates and that of displacement. Concerns regarding the self-perpetuation of large fortunes are directly related to the relative magnitude of incumbent growth rates, which are distinct from the growth of top wealth shares.

Several papers have addressed the role of idiosyncratic wealth shocks in top wealthy households. My paper further extends the literature on the rise of top wealth shares by accounting for persistent differences in growth rates across households. Using detailed Swedish administrative data, Fagereng, Guiso, et al. (2016) document the importance of idiosyncratic risk for explaining dispersion in wealth growth of top wealth brackets. They find that heterogeneous returns can explain most of the time-variation in Swedish top wealth shares from 2000 to 2007. Consistent with their finding, I find the relative role of incumbent growth in driving changes in wealth inequality is larger at short horizons.

My paper also relates to the theoretical literature characterizing wealth inequality given an underlying stochastic process for wealth. My paper quantifies a qualitative insight of Gabaix et al. (2016), which is that the rapid increase in wealth inequality cannot be explained solely by changing growth rates of wealth. Less than one fifth of the increase in the Forbes wealth share is the result of high growth rates of wealth. An additional insight of their paper is that incorporating high-growth types that rapidly climb the ranks of the wealth distribution can generate fast transition dynamics. These high-growth individuals are analogous to the new entrants that I measure in my data set.

The paper closest to mine is Gomez (2018), which decomposes the rise in wealth inequality into within and displacement terms. Our theoretical frameworks differ in that he assumes a homogeneous growth rate of wealth among top wealth households, whereas I allow for persistent heterogeneity in growth rates. In Section 2.2, I elaborate on the differences in our methodologies. Conceptually, the differences stem from the fact that I follow a fixed population of households over time in calculating the growth rate of incumbent wealth. Thus, my growth rates can be interpreted as the growth rate of wealth for an incumbent

wealthy household over time, rather than chained one-year growth rates of current Forbes 400 members. His paper also differs from mine in the statistical method used to impute wealth of missing households. I do this by creating a panel of wealth for Forbes 400 households and measuring realized growth rates in the panel. Gomez (2018) uses a Kaplan-Meier estimator to infer unobserved growth rates based on the distribution of observed returns in the Forbes 400. I show that, in the presence of heterogeneous growth rates, estimates of growth rates from repeated cross sections are biased estimates of individual household growth rates.

An empirical contribution of my paper is the construction of a panel data set of wealth for Forbes 400 households. I do this by merging observations from several existing data sets of wealth estimates. I impute missing observations using real estate ownership data from the LexisNexis public records data set. The data set has been used in the finance literature to investigate questions related to corporate leverage (Cronqvist, Makhija, and Yonker, 2012) and CEO succession (Yonker, 2017). Another paper that uses real estate value as a proxy for household wealth is Koudijs and Salisbury (2016). In a similar spirit, Civale, Diez-Catalan, and Salgado (2017) uses equity holdings as a proxy for household wealth within the Forbes 400.

My measured wealth dynamics are the realized value of an underlying portfolio. Previous papers including Calvet, Bach, and Sodini (2015), Fagereng, Guiso, et al. (2016), and Fagereng, Holm, et al. (2019) have characterized wealth dynamics in European countries, whereas my focus is on American households and American wealth inequality. While these papers rely on administrative data, I construct a panel data set to estimate these dynamics for wealthy American households in the absence of analogous data. Earlier work on wealth inequality in the United States has used repeated cross sectional data sets such as the Survey of Consumer Finances (Benhabib, Bisin, and Luo, 2015) and estate tax filings (Kopczuk and Saez, 2004). Rather than estimate wealth dynamics from repeated cross-sections, I construct a panel to directly estimate growth rates of wealth, thereby avoiding the need for structural assumptions relating the cross-sectional wealth distribution to the underlying

data-generating process. My results are the first estimates of long run wealth dynamics for wealthy American households. My work on rising wealth inequality is complementary to studies of rising income inequality in the United States (Guvenen, Ozkan, and Song, 2014; Song et al., 2018).

My paper contributes to the asset pricing literature that relates the wealth distribution to observed asset prices. Papers that discuss the effect of heterogeneity on asset prices include Gârleanu and Panageas (2015) and Gomez et al. (2016). In those papers, ex-ante heterogeneity drives changes in the wealth distribution as well as changes in risk premia due to time variation in risk-bearing capacity following strings of good and bad shocks. These models predict that wealthy individuals invest more aggressively and grow faster than aggregate wealth, resulting in increasing wealth inequality. This is at odds with my empirical finding that wealth inequality has increased significantly while wealthy households have outpaced aggregate wealth only modestly.

I find that wealth dynamics of wealthy households feature heterogeneous growth rates and idiosyncratic shocks. These features parallel those present in random growth models of firms, which have been used to explain the size distribution of firms (Luttmer, 2007). Furthermore, the large role of displacement is consistent with an increasingly skewed distribution of new firms (Gârleanu, Kogan, and Panageas, 2012; Gârleanu and Panageas, 2017) and an increase in idiosyncratic volatility (Herskovic et al., 2016; Hartman-Glaser, Lustig, and Xiaolan, 2017). At the aggregate level, it is also closely tied to the rise of superstar firms (Autor et al., 2017). Some papers that analyze the impact of concentrated ownership of firms on asset prices include Haddad (2012) and Di Tella (2019). Peter (2019) studies the role of firm dynamics and financing frictions in explaining cross-country differences in wealth inequality. Campbell, Ramadorai, and Ranish (2018) studies the equity portfolios of Indian households and find evidence of heterogeneous returns arising from concentrated equity positions.

My findings on family wealth dynamics are complementary to the literature on family firm dynamics (Bennedsen et al., 2007; Bertrand and Schoar, 2006). A majority of individuals

in the Forbes 400 are associated with a family firm, and a number of papers study the impact of family ownership on firm outcomes (Anderson and Reeb, 2003). Pérez-González (2006), Villalonga and Amit (2006), and Morck, Stangeland, and Yeung (2000) show that lower performance of family firms arises in part due to within-family transition of managerial roles. My finding that incumbent wealthy households have quite ordinary growth rates of wealth echoes these results on firm management in an adjacent economic setting.

My work also contributes to the literature on inter-generational mobility (Clark and Cummins, 2013; Barone and Mocetti, 2016). In the long run, economic mobility is affected by both wealth dynamics within an individual’s lifetime, as well as inter-generational transfers. I find that incumbent households’ wealth share has increased over time, meaning that “old-money” has self-perpetuated over the past thirty years. However, I also find evidence that older cohorts of wealthy families under-perform newer cohorts. Overall, the self-perpetuation of wealth is not the driver of the sharp increase in wealth inequality over the past 30 years.

The rest of the paper is organized as follows: In Section 2, I present a model of wealth inequality and asset prices. In Section 3, I outline the data sources and methodology used to construct my panel data set, and then apply my framework to decompose the rise in the top wealth share. In Section 4, I discuss how my findings present challenges for standard macro-finance models and propose extensions.

## 2 Theory

To clarify concepts and motivate the measurement of cohort growth rates, I now layout an economy in which the long run wealth growth of agents, rather than the wealth growth of a percentile of the wealth distribution, determines the interest rate in the economy. I show that wealthy inequality driven by displacement leads to lower rates of return and higher asset prices, whereas superior incumbent growth rates leads to higher rates of return.

The key ingredients in the model are a life-cycle profile of firm dynamics and borrow-

ing constraints. The borrowing constraint prevents entering agents with high expected wealth growth from fully borrowing against their future income, so that these agents are not marginal in determining interest rates.

The model features no aggregate risk and there is only a single traded asset, a riskless bond. As I show, even in this framework, the source of wealth inequality matters for asset prices. Thus, the effect of wealth inequality of asset prices likely generalizes to setups featuring a richer portfolio choice problem, but which I am forced to abstract from for the sake of tractability. My preferred interpretation is that the interest rate in this economy measures the returns on tradable wealth.

## 2.1 Model

At time  $t_0$ , the economy is populated by a continuum of agents  $i$ . Each agent owns a firm paying dividends at rate  $y_i$ . Initially, the dividend of each agents' firm grows at a high rate  $\mu^H$ . However, each firm is risky in the sense that high growth firms can decay and become low growth firms with growth rate  $\mu^L < \mu^H$ . This decay occurs according to a Poisson process with instantaneous intensity  $\lambda dt$ . By the law of large numbers, aggregate dividends are deterministic and there is no aggregate risk. Agents in the economy have log preferences and seek to maximize expected utility given subjective discount parameter  $\rho$

$$U(\{c_t\}) = \mathbb{E} \int_0^\infty e^{-\rho s} \log c_s ds$$

where the expectation is taken over both the transition time and the death time experienced by the agent.

Agents are born at rate  $\delta$  owning firms whose initial dividend  $Y$  is drawn from a distribution with mean  $\kappa Y$ . The exact distribution of new firm dividends will affect the stationary wealth distribution in the economy, but not the main results presented, which hold for any positive support distribution with mean  $\kappa Y$ . Agents are in a state of perpetual youth and

low-growth agents die at an i.i.d rate  $\delta$ . Firms of deceased agents do not disappear, but instead continue to grow and produce output for consumption. Figure 2 plots a potential sample path for a firm with initial dividend  $y_0$ . Up to time  $t_\lambda$ , the firm grows at rate  $\mu^H$ , and grows at rate  $\mu^L$  forever after, even though the founder passes away at time  $t_\delta$ .

As in Blanchard (1985), I assume that a competitive annuity market exists which redistributes the wealth of deceased agents proportionately among surviving agents according to their wealth. This assumption serves to allow agents to perfectly hedge their individual mortality risk. The law of motion of total output  $Y$  in this economy is given by

$$\frac{dY}{Y} = \left( \mu^H x + \mu^L (1 - x) + \delta \kappa \right) dt \quad (1)$$

where  $x$  denotes the output share of high growth firms,  $x = \frac{Y^H}{Y}$  and  $Y^H$  denotes total output of firms with high dividend growth rates. The laws of motion of total output of high- and low- growth firms are

$$\frac{dY^H}{Y^H} = \left( \mu^H + \frac{\delta \kappa}{x} - \lambda \right) dt \quad (2)$$

$$\frac{dY^L}{Y^L} = \left( \mu^L + \lambda \frac{x}{1 - x} \right) dt \quad (3)$$

Over an interval  $dt$ , high type firms' output grows by  $\mu^H$  and a fraction  $\lambda dt$  of the high type firms transition and become low growth firms. Newly entering agents owning firms with aggregate dividends  $\delta \kappa Y$  further increase the growth rate of high type output. For low type output, incumbent firms' output grows by  $\mu^L$ , and output is further increased by the arrival of transitioning firms into the low growth state. As firms do not disappear upon the founder's death,  $\delta$  does not appear in the growth rate of  $Y^L$ . Displacement in this economy proceeds deterministically, wherein new firms are born at a constant rate and comprise a constant share of aggregate output. I now introduce a borrowing constraint which limits the high type agents' participation in financial markets. Under no-trade, these agents consume

the dividends of their firms, which grow at rate  $\mu^H$ . The high-type agents would like to borrow against their firms in order to smooth consumption. The dividend yield is relatively low for high growth firms, and thus in autarky, these agents under-consume relative to their total wealth. On the opposite extreme, absent frictions, the low-type agents would lend to the high-type agents and expected consumption growth would be equalized across all agents. Agents owning high growth firms over-consume in the short term, finance their excess consumption with loans, and repay these loans once their firms transition to the low growth state. The constraint limits this by restricting high type agents' ability to borrow. Specifically, I impose that agents cannot sell their firms and cannot credibly promise to repay more than proportion  $\alpha$  of their dividend income  $y$ . The problem of a high growth agent a firm paying dividend  $y$  and loan balance  $l$  is therefore

$$\begin{aligned}
V^H(y, l) &= \max_c \left\{ \int_0^\tau u(c) dt + e^{-\rho t} \left( e^{-\lambda dt} V^H(y', l') + (1 - e^{-\lambda dt}) V^L(y', l') \right) \right\} & (4) \\
\text{s.t.} \quad \mathbb{E}_t \int_0^\tau e^{-rs} (c_{t+s} - y_{t+s}) ds &\leq \alpha y_t \quad \forall t, \tau \\
y' &= y (1 + \mu^H dt) \\
l' &= l (1 + r dt) + (c - y) dt
\end{aligned}$$

Low type agents are repaying their loans and lending to current period high type agents. A low growth agent is therefore unconstrained by the borrowing limits and solves the problem

$$\begin{aligned}
V_L(y, l) &= \max_c \left\{ \int_0^\tau u(c) dt + e^{-(\rho+\delta)dt} V_L(y', l') \right\} & (5) \\
\text{s.t.} \quad y' &= y (1 + \mu^L dt) \\
l' &= l (1 + r dt) + (c - y) dt
\end{aligned}$$

**Definition 1.** *A symmetric steady-state equilibrium consists of agent masses  $m_H$ , and  $m_L$ , an interest rate  $r$ , and consumption policies  $c_i$  for  $i \in \{H, L\}$  such that*

1. *Agent masses are constant over time*

2. *The borrowing and consumption policies solve the optimization problem of high- and low-type agents, taking agent masses and the interest rate as given*
3. *The consumption market clears*
4. *The lending market clears*

In steady state, a fraction  $\frac{\delta}{\delta+\lambda}$  of firms will be in the high growth rate, and a fraction  $\frac{\lambda}{\delta+\lambda}$  will be in the low growth state. For the economy to be stationary, the output of high- and low-growth firms must grow at the same rate. When low-growth firms make up a smaller fraction of the economy, their lower intensive growth rate is supplemented by a high extensive margin of growth coming from decaying high-growth firms.

**Proposition 1.** *The steady state output share of high growth firms is*

$$x = \frac{\sqrt{(\delta\kappa - \mu_H + \lambda + \mu_L)^2 + 4\delta\kappa(\mu_H - \mu_L)} - (\delta\kappa - \mu_H + \lambda + \mu_L)}{2(\mu_H - \mu_L)}, \quad (6)$$

and output growth is given by

$$g_Y = \mu_H - \lambda + \frac{\delta\kappa}{x}. \quad (7)$$

Furthermore, the steady state output share of high type firms is decreasing in  $\mu^L$  and in  $\lambda$ , and increasing in  $\kappa$ :

$$\frac{dx}{d\mu^L} = -\frac{1-x}{\mu^H - \mu^L + \delta\kappa/x^2} < 0, \quad (8)$$

$$\frac{dx}{d\lambda} = -\frac{1}{\mu^H - \mu^L + \delta\kappa/x^2} < 0, \quad (9)$$

and

$$\frac{dx}{d\kappa} = \frac{\delta + \kappa/x}{\mu^H - \mu^L + \delta\kappa/x^2} > 0, \quad (10)$$

Intuitively, the steady state output share of high type firms is higher when low type firms grow slowly,  $\frac{dx}{d\mu^L} < 0$ , and is lower when new firms spend less time as high type firms,  $\frac{dx}{d\lambda} < 0$ .

**Solution to the Low Type’s Problem** Under the assumption of log preferences, the low type agent finds it optimal to consume a constant fraction  $\rho + \delta$  of her total wealth, given by the value of her firm plus her financial wealth

$$w = \frac{y}{r - \mu^L} + l$$

so that her net growth rate of total wealth is  $r - (\rho + \delta)$ . Even though firms cannot be bought or sold among living agents, firms can be priced via a no-arbitrage relationship which implies that the value of a low growth firm is the discounted present value of a growing perpetuity. The results are entirely unchanged if the setup is modified to allow for the purchase and sale of low type firms. High type agents are constrained and would not purchase these firms, while low type agents are indifferent between owning their personalizing growing perpetuity or a basket of identical growing perpetuities.

**Solution to the High Type’s Problem** High-growth agents will find it optimal to always be at the leverage constraint  $\alpha y$ . An agent who does so has locally deterministic consumption growth of  $\mu^H$  whereas the borrowed amount grows at rate  $r$ . Thus, she will borrow the maximum amount as long as  $\mu^H > r - \rho$ . For an agent who does not borrow up to the constraint, they can increase their utility by borrowing  $\varepsilon$  more today at rate  $r$ , consuming it, and repaying  $\varepsilon e^{r dt}$  out of tomorrow’s dividend. I provide a formal proof in Appendix B.

Given that the decay rate is i.i.d and the leverage constraint is proportional to dividends  $y$ , this argument is independent of the current level of dividends and holds for all high-growth agents. Thus, high growth agents consume in excess of their income. Conditional on remaining a high-type, they have consumption growth equal to  $\mu^H$ , and their consumption-dividend ratio is given by  $1 + \alpha (r + \lambda - \mu^H)$ .

The leverage constraint will bind as long as it prevents agents from consuming their optimal amount. This optimal amount corresponds to the consumption-income ratio of a

newborn agent who was free to sell her firm and reinvest at the prevailing interest rate  $r$ . Under log preferences, the agent will consume a constant fraction  $\rho$  of her wealth, which is given by

$$\frac{y}{r - \mu^L} \frac{\lambda + r - \mu^L}{\lambda + r - \mu^H} \quad (11)$$

Therefore, the constraint always binds in equilibrium as long as

$$1 + \alpha (r + \lambda - \mu^H) < \frac{\rho}{r - \mu^L} \frac{\lambda + r - \mu^L}{\lambda + r - \mu^H} \quad (12)$$

and the consumption of a high type agent owning firm with current dividend  $y$  is given by  $\epsilon y$ , where

$$\epsilon := \min \left\{ 1 + \alpha (r + \lambda - \mu^H), \frac{\rho}{r - \mu^L} \frac{\lambda + r - \mu^L}{\lambda + r - \mu^H} \right\}$$

In either case, consumption conditional on remaining in the high growth state grows at rate  $\mu^H$ . The equilibrium interest rate  $r$  affects the consumption-income ratio of high type agents, but not the growth rate of consumption.

**Financial Markets** New loans are made to finance high type consumption at rate  $(\epsilon - 1) Y^H dt$ .

These loans accrue interest and are repaid by agents after their firms transition to the low growth state. By the law of large numbers, fraction  $\lambda dt$  of high type firms decay over interval  $dt$ , and the agents owning those firms have loans in aggregate totaling  $\lambda L dt$ . The law of motion for loans outstanding to high type agents is given by

$$dL = ((r - \lambda) L + (\epsilon - 1) xY) dt \quad (13)$$

and total wealth of low type agents is the sum of loans outstanding and value of all current low type firms

$$W^L = \frac{(1 - x) Y}{r - \mu^L} + L \quad (14)$$

**Proposition 2.** *In steady-state, the net wealth of low type agents is given by*

$$W^L = \left( \frac{1-x}{r-\mu_L} + \frac{\epsilon-1}{g+\lambda-r} x \right) Y \quad (15)$$

*The interest rate  $r^*$  satisfies the market clearing condition*

$$\epsilon x + (\rho + \delta) \frac{W_t^L}{Y} = 1 \quad (16)$$

*By Walras' law, once the consumption market clears, the lending market will also clear.*

Proposition 2 states that the wealth of low type agents is given by the value of the low growth firms in the economy, plus the value of loans outstanding to high type agents. In equilibrium, there are also some outstanding loans made to former high type agents that have yet to be repaid, but these are simply transfers among the low type agents and do not affect the aggregate wealth of low type agents. The interest rate in the constrained economy is determined by consumption market clearing. Too low an interest rate results in excess demand, as low types seek to consume a constant fraction of their wealth. As the interest rate increases, these agents prefer to save and enjoy the higher rate of return. In the opposite case, too high an interest results in a demand shortage as low types prefer to save rather than consume, and thus the interest rate needs to decline to encourage low type agents to consume more.

## 2.2 Growth Rates

Fixing a cohort, the log growth rate of cohort wealth, which I refer to as a *cohort growth rate*, is given by

$$\frac{1}{t} \log \frac{W_t}{W_0} = e^{-\lambda t} (\mu^H - \rho) + \frac{1}{t} \int_0^t (rt - (\rho + \delta)t + (\mu^H + \delta - r)s - \ln \varphi) \lambda e^{-\lambda s} ds \quad (17)$$

$$= r - (\rho + \delta) + \frac{1 - e^{-\lambda t}}{\lambda t} (\mu^H - \rho - r - \lambda \ln \varphi) \xrightarrow{t \rightarrow \infty} r - (\rho + \delta) \quad (18)$$

where

$$\varphi = \frac{\lambda + r - \mu^L}{\lambda + r - \mu^H}$$

is the ratio of the value of a high-growth firm to the value of a low-growth firm with the same level of dividends. Thus, in this economy the cohort growth rate reveals the returns on financial wealth and tradable assets.

Agents' wealth growth is characterized by a period of high initial growth followed by modest growth in the long term. Figure 3 plots the stationary distribution of wealth in this economy, distinguished between high type and low type agents. High type agents are wealthier on average and over-represented in the upper tails of the wealth distribution. Measurements of wealth growth done using repeated cross-sections of a top percentile above threshold  $q$ , as in Gomez (2018), can be written as

$$\sum_{j \in \{H, L\}} \mu^j \int_{q_t}^{\infty} f^j(w_t) dw_t$$

where  $f$  is the joint density of growth rates and wealth. In a stationary economy, the distribution  $f$  is invariant over time and thus the measured wealth growth is constant over time. In particular, these measured growth rates are a function of  $\mu^H$ , whereas the cohort growth rate, and asset prices, are only a function of  $r$ . In this economy,  $\mu^H > r$ , and so measurements based on repeated cross sections will over-estimate the long-run growth rate of wealth due to the transition dynamics. Wealthiest households today will always have a high growth rate, yesteryear's wealthy households have transitioned and now grow at a rate reflecting asset returns. This is equivalent to saying that the wealth dynamics captured by cohort growth rate converge to the wealth dynamics of the marginal agent, while measurements from repeated cross sections are biased at all horizons. Figure 4 plots the relative population of high type agents above a cutoff level of wealth,  $\mathbb{P}[\mu = \mu^H \mid W \geq w]$ , when the distribution of new firm dividends is exponential. The growth rate estimated from repeated cross sections is significantly higher than the true long run growth rate of a cohort,

and this bias is independent of horizon.

Importantly, the use of cohort growth rates is valid even in the absence of transition dynamics. Such a case can be modeled either by eliminating the motive to borrow through equating  $\mu^L$  and  $\mu^H$ . In this case, every agents' wealth grows at  $r$  less consumption as every agent is marginal in the bond market. Thus, the use of cohort growth rates is a more robust method of determining the stochastic discount factor, as it recovers the right discount factor in the friction-less case as well as in the case of constrained agents. In addition, cohort growth rates are valid even when the econometrician cannot directly observe which agents are constrained. When agents know their type but the econometrician does not, cohort growth rates are robust to selection biases, as all agents decay to the low type in the long run.

### 2.3 Wealth Inequality and Asset Prices

Within the model, the contribution of new entrants and incumbents to rising wealth inequality is governed by two parameters. Wealth accumulation by new entrants is increasing in  $\kappa$ , the output share of new firms. When new firms are more valuable, the agents who own those firms are the wealthiest agents in the economy. On the other hand, wealth accumulation by incumbents is increasing in  $\mu^L$ , the growth rate of old firms. In the model, these firms' growth rates determine the investment opportunities available to low type agents. When these investment opportunities are comparatively valuable, the wealthiest agents in the economy are those who were born with valuable firms and had the good fortune to live for a long time, accumulating wealth all the while. I now examine the effect that a relative shift in these parameters has on interest rates. I show that while rising wealth inequality driven by new entrants results in a decline in the interest rate, increasing wealth inequality driven by incumbents results in an increase in the interest rate. Both an increase in  $\kappa$  and an increase in  $\mu^L$  have the effect of increasing estimates of wealth growth constructed using repeated cross sections, but, as shown in Figure 5, the interest rate falls when displacement,

captured by  $\kappa$ , increases. Cohort growth rates accurately reflect this decline in incumbent households' wealth growth. This further motivates my empirical methodology of estimating cohort growth rates using panel data.

## 3 Empirics

In this section, I detail the construction of my data set and present the results of analysis using that data set. I present the data sources used in Section 3.1. I detail how I combine the different data sources into a single panel in Section 3.2. I detail the aggregation of individual observations into populations of entry and incumbent cohorts in Sections 3.3 and 3.4, respectively. I present findings in Section 3.5.

### 3.1 Data

The initial construction of my panel begins with the Forbes 400 data set, published annually since 1982. By starting with Forbes 400 lists, I have a number of repeated observations for the same individual over many years. The data collection challenge of this paper is to fill in wealth observations missing in the Forbes 400 lists.

**Forbes Dropoff Lists** In order to account for dropouts from the Forbes 400, I employ a number of data sources. The first auxiliary data set is Forbes Magazine's own published list of drop offs, beginning in 2012. For all subsequent Forbes 400 lists, Forbes Magazine reported the wealth of individuals who were removed from the list on the grounds that they were no longer among the 400 richest Americans. I manually collect these reports from archives of Forbes' website. The weaknesses of this data set are that: (i) it only exists since 2012, (ii) it only contains wealth for dropoffs in the year immediately following their exit from the Forbes 400 list, and (iii) it does not report wealth for deceased individuals.

**Forbes Billionaire Lists** The second auxiliary data set is Forbes Magazine’s published list of world-wide billionaires. This list was first compiled in 1996, and continues to this day. I scraped the historical Forbes Billionaire lists from archives of Forbes’ website. Individuals who fall off the Forbes 400 list, but who remain billionaires, stay in the Forbes Billionaire data set. This is the case for a number of individuals, and I am able to combine the data sets to create a balanced panel of wealth for these individuals extending through to 2018. Another advantage of the Forbes Billionaire list is that it assists me in estimating the wealth of deceased Forbes 400 individuals.

**Family Structures for Forbes 400 members** In order to identify family members, I manually collect data on the names and, where possible, age and location of children and spouses of Forbes 400 individuals. Consistent with Bernstein and Swan (2008), I find that the average Forbes 400 individual has three children. I hand collect data on the number and the names of children using a variety of internet data sources. For deceased Forbes 400 members, their obituaries often contain information on surviving family members. Even for surviving individuals, or individuals for whom I could not locate an obituary, it is possible to obtain names of family members using obituaries of close relatives.<sup>1</sup> In total, I identified 4,843 children of Forbes 400 members, and found names and other information for 4,578 of those children. A detailed list of sources used in the construction of this data set is available upon request.

**LexisNexis Property Records** In order to account for individuals not found in the Forbes data sets, due either to dropping off prior to 2006 or dropping to below \$1 billion in net worth, I make use of the LexisNexis Public Records data set. LexisNexis offers a

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<sup>1</sup>In some cases, Forbes 400 members or their spouses have written books and included dedications to their children. This is the case for, among others, Robert and Janice Davidson, as well as David Shaw. The Davidsons wrote *Genius Denied: How to Stop Wasting Our Brightest Young Minds*. David Shaw’s wife Beth Kobliner wrote *Make Your Kid A Money Genius (Even If You’re Not): A Parents’ Guide for Kids 3 to 23*. More esoteric examples include Pincus Green, whose children jointly wrote a letter to then-president Bill Clinton requesting a presidential pardon for their father.

search interface through which I can observe basic biographical information, along with address history and property records, for a significant proportion of the American population. Starting with the biographical information included in the Forbes 400 lists, I search for individuals in the LexisNexis database based on name, approximate age, and state of residence. From there, I reject potential matches based on employment history and family information. Through this process, I manually link 1,565 Forbes 400 individuals to a unique LexID.

For each of the 1,565 Forbes 400 individuals that I am able to uniquely identify in LexisNexis, I download all property deeds and property assessments pertaining to that individual, as well as the names and addresses of all likely family members. For each likely family member, I then find the most likely matched LexID corresponding to that individual in the LexisNexis database, based on biographical information, and download all property deeds and assessments pertaining to these potential family members. I aggregate property records at the family unit, so that all family members' property records are grouped together. I further process the property records data to account for duplicates and potentially mis-labeled records using two methods. First, I exclude non-apartment properties sharing identical GPS coordinates. Second, I exclude any remaining properties which feature substantially similar parcel numbers. Finally, I use textual analysis to exclude commercially zoned properties.

**Wealth-X Profiles** The final non-standard data set that I use to produce my panel consists of Wealth-X profiles on ultra-wealthy individuals, defined here as individuals with net worth exceeding \$30 million as of 2018. The profiles are maintained by dedicated staff employed by Wealth-X, and contain information derived from publicly disclosed transactions, holdings, philanthropy, conspicuous purchases, board memberships, professional and family ties, and other biographical information. I first extract a list of all ultra-wealthy individuals, both foreign and domestic, in the Wealth-X database. Based on this list of individuals, I then collect each profile and extract family details and portfolio holdings. Thus, my data set contains every individual Wealth-X has identified as having a net worth exceeding \$30

million in 2018. In this paper, I principally focus my attention on domestic ultra-wealthy individuals, and thus discard all individuals with no business or residential addresses within the United States. I then manually match these individuals to Forbes 400 family units based on the hand-collected family structure information.

## 3.2 Methodology

In this Section, I discuss the procedure by which I combine different data sets into a single panel of household wealth. I begin with the Forbes 400 lists, and combine family units so as to minimize the contribution of death and bequests. Thus, in any year that a family appears in the Forbes 400, I take the Forbes 400 wealth to be the total wealth of that family. I now begin filling in missing observations from the panel of wealth. Starting from the year a family first enters the Forbes 400 list, I impute missing observations using the Forbes Dropoff lists, the Forbes Billionaire lists, and my estimates based on the family’s residential property holdings.

For individuals and families who exit the Forbes 400 after 2012, the Forbes Dropoff list contains a single additional observation in which Forbes Magazine staff estimate their wealth. This estimate is the basis of Forbes’ decision to exclude the individual. Whenever available, I fill in missing observations using these reported values. For the remaining observations, I first attempt to fill in missing wealth observations using data from the Forbes Billionaire lists, which go back as far as 1996. Even in the post 2012 period, the Forbes Billionaire list contributes to filling in missing observations for individuals who exit due to death and for any years following the year of immediate exit from the Forbes 400.<sup>2</sup>

To fill in the remaining missing observations, I use estimates of the family’s residential portfolio holdings, collected from LexisNexis, to impute a wealth value for each missing observation. I impute missing wealth observations from housing value observations. For each household  $i$ , I collect the first record date  $t_{ij}^{\text{start}}$  and final record date  $t_{ij}^{\text{end}}$  for each piece

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<sup>2</sup>Forbes Magazine’s Dropoff lists do not report wealth for deceased members of the Forbes 400.

of residential property  $j$  associated with any household members identified in LexisNexis. I then collect housing values  $h_{ij}$  for years  $t \in [t_{ij}^{\text{start}}, t_{ij}^{\text{end}}]$  by using the most recent property valuation. In cases in which purchase and/or sale price from deed records are available, I exclusively use those prices, rather than relying on more recent property assessments.

I aggregate property values at the household level by summing the value of all properties  $j$  owned by household  $i$  in year  $t$  to arrive at a total housing value  $H_{it}$ :

$$H_{it} := \sum_j h_{ijt} \mathbb{I}_{[t_{ij}^{\text{start}}, t_{ij}^{\text{end}}]}(t).$$

I then use the panel of total housing values to impute unobserved wealth observations based on the following definition

$$\hat{W}_{it} := W_{is}^* \left( \frac{H_{it}}{H_{is}} \right)^\varepsilon, \quad s := \max \{ \tau \leq t \mid W_{i\tau}^* \text{ exists} \}, \quad (19)$$

where  $\varepsilon = 1$  in my primary specification. In Appendix D, I discuss the economic assumptions motivating this imputation and elaborate on the strengths and weaknesses of this imputation method. The imputation procedure using real estate can be described in simple terms: for a given year  $t$  in which I observe housing values  $H_{it}$  for household  $i$ , but not wealth  $W_{it}^*$ , I estimate that the unobserved household wealth is equal to last known value of wealth from year  $\tau$ , multiplied by the percentage increase in the household’s housing value between years  $\tau$  and  $t$ .

### 3.3 Cohort Identification and Aggregation

Using the methodology described above, I construct a survival bias-free panel of wealthy individuals. A primary contribution of my paper is the decomposition of wealth inequality, and in particular documenting heterogeneous contributions to increasing wealth inequality. To focus on this heterogeneity, I group Forbes 400 households by their year of entry into the Forbes 400. This corresponds to the “birth” of the cohort in the model, and represents

the earliest point in time for which I have wealth estimates for each household. I further aggregate cohorts at the five year horizon, so that my first cohort corresponds to households which entered the Forbes 400 between 1982 and 1986, the second cohort contains households which entered between 1987 and 1991, and so on. Summary statistics on the coverage of my panel are show in Table 1. Figures 6 and 7 present binned scatter plots of cohort-level wealth growth against cohort-level real estate growth at the five- and ten-year horizon, respectively, for individuals within each entry cohort that remained on the Forbes 400 list. The relatively good fit motivates the assumption of a constant portfolio share in real estate. These figures are conditional on the household remaining on the Forbes 400 list, so that it is possible to calculate their realized growth rate of wealth, independent of any imputation procedures.

As discussed in Section 2, cohort growth rates are a robust means of measuring household growth rates of wealth in the presence of constraints and heterogeneity. In addition, there are two statistical reasons to aggregate households at the cohort level. First, while there are approximately 1,400 distinct households in my panel, almost 400 of these households entered the list in the inaugural publication of the Forbes 400 list. Thus, there are on average less than 30 households which enter the Forbes 400 in a given year. In such a small population, idiosyncratic wealth shocks still play a large role, and thus the wealth dynamics of small cohorts are imprecisely measured in the data. The concern here is a cross-sectional one; I want to compare long run growth rates across cohorts, and thus my estimates need to be precise enough to distinguish trends across cohorts. The second reason is that my focus is on long run growth rates of wealth, and thus combining cohorts simplifies the time-series analysis. An alternative specification featuring overlapping yearly fixed effects and cohort effects would both complicate the analysis and limit my statistical power by introducing many more degrees of freedom.

### 3.4 Incumbent Identification and Aggregation

In every year, the top wealth percentile is populated by individuals from multiple entry cohorts. To measure the contribution of this incumbent population to rising top wealth shares, I group households based on the years they appear in the Forbes 400 list. In year  $t$ , all households that appeared on the Forbes 400 list in the prior five years are included in the year  $t$  incumbent population, and I measure incumbent wealth at time  $t$  as of year  $T$  as the total wealth of this fixed set of households as of year  $T$ . With the exception of the 1986 incumbent population, this is different from the year  $t$  entry cohort.

Using entry cohorts as the unit of analysis is useful when the interest is in documenting heterogeneous growth rates. There the identification strategy is essentially to compare contemporaneous realized growth rates across entry cohorts. However, for estimating the displacement term, the incumbent wealth growth rate is a sufficient statistic for the joint distribution of cohort growth rates and wealth shares. I present results based on yearly incumbent populations and compare the growth rate of several incumbent cohorts to the rise in wealth inequality over five-year staggered periods.

### 3.5 Results

I now present cohort growth rates estimated from my panel data set. A key finding is that older cohorts have lower growth rates compared to newer cohorts. I show this in several ways. I first compare average rates of return over the entire sample. I then compare contemporaneously estimated rates of return between different cohorts. This heterogeneity is consistent with the life cycle dynamics introduced in my model, in which younger households own the high growth firms, but decay to the low growth state over time.

Table 2 presents the five year wealth growths rate of each entry cohort of Forbes 400 households, along with the long-term growth rate of that cohort from its inaugural year through 2018. Older cohorts tend to have lower growth rates than newer cohorts. A notable exception is the 2001 cohort, which featured a number of dot com entrepreneurs who

remained on the Forbes 400 for only a short period of time.

Later cohorts in my panel are only observed in the period after entering the Forbes 400. This makes comparing full-sample growth rates insufficient for identifying heterogeneous growth rates, as the sample averages are confounded by aggregate market returns in periods prior to a cohort's appearance in my panel. A potential explanation for these differences in sample averages could be that wealthy households all have a growth rate of wealth, driven by equity holdings, and that stock market returns were low in the late 1980's, and have progressively improved since then. Such a data-generating process would be consistent with common growth rates of wealth, yet different observed sample averages.

I account for time-varying drivers of growth rates in two different ways. The first approach is consistent with a concern that equity holdings, along with time-varying stock market returns, are driving my estimates. I run regressions on residuals of wealth growth after controlling for a time-invariant market loading. The specification is

$$\mu_{st} = \beta^{\text{Mkt}} \text{Mkt}_t + \beta_s + \varepsilon_{st},$$

where Mkt corresponds to the July through June Fama-French market factor return.<sup>3</sup> Effectively, I subtract 0.4 times the periods' Fama-French market factor return from each cohort-year observation. The coefficient of 0.4 comes from regressing my estimates of wealth growth against the market factor, and explains a substantial component of the time-variation in growth rates. Wealth individuals saw their wealth decline in down market periods such as the late 1990's and late 2000's. Results from regressing market-neutral wealth growth on cohort fixed effects are presented in Table 3, Column (3). I still find that older cohorts' wealth grows at a slower rate than that of younger cohorts.

The second way in which I account for time-varying common growth rates is the inclusion

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<sup>3</sup>I use July through June to better line up with the publication of the Forbes 400 lists.

of year fixed effects in my regressions. The specification is

$$\mu_{st} = \alpha_t + \beta_s + \varepsilon_{st}$$

This method is silent on the factors driving time-varying growth rates of wealth. A limitation of this approach is that the level of the cohort fixed effects  $\beta$  cannot be disentangled from the level of the time fixed effects  $\alpha$ . Results of these regressions, run at both one- and five-year horizons, are also reported in Table 3. With the exception of the five-year returns, all specifications estimate that younger cohorts grow faster than older cohorts. As a consequence of my normalization, the level of the coefficients in Columns (2) and (4) are not informative, and the appropriate test for heterogeneous growth rates is to look at the relative ordering of the cohorts, as well as the magnitude of the differences in returns, rather than the levels of the returns. In the case of Column (2), in which I conduct my analysis at the five-year horizon, it is only the newest 2006-2011 cohort that under-performs the oldest cohort. The overall trend is consistent across these different specifications.

The observed trend across the regressions suggests that age could be a likely contributor to this effect. I investigate the role of age by augmenting my regression specification to include cohort age effects alongside the common time-varying component and the cohort-specific growth rates. I report results of these specifications in Table 4. Column (1) corresponds to the specification

$$\mu_{st} = \beta^{\text{Mkt}} \text{Mkt}_t + \text{Age}_{st} + \varepsilon_{st},$$

where age is the number of years since that cohort's birth year,  $s - t$ . The economic interpretation of the coefficient is that the cohort that entered the Forbes 400 list at time  $t - 5$  under-performs the time  $t$  cohort by 0.2 percentage points per annum. The oldest cohort in my panel entered in 1986, and the youngest cohort entered in 2011. From these results, I would predict that the 1986 cohort grows 1 percent slower each year than the 2011 cohort. This is compared to a difference in growth rates of 1.4 percentage points when comparing the

sample averages reported in Table 2, and is within the range of estimates presented in Table 3. The effect is not driven by the choice of the 1986 and 2011 cohorts. To show this, I substitute the linear age effect for a sequence of age indicator variables, binned at the five year level. The results are reported in Column (2). With the exception of the very oldest cohort, I find a stable monotonically decreasing relationship in age. Furthermore, the magnitude of the difference in age fixed effects is similar to the coefficient from the linear specification. The coefficients are unchanged when I re-introduce cohort fixed effects. I report results for the linear specification including cohort fixed effects in Column (3), and for the fixed effects specification including cohort fixed effects in Column (4).

The presence of heterogeneous growth rates has quantitative implications for the estimation of long term growth rates and displacement. The growth rate of wealthy households at time  $t$ , and consequently the growth of the wealth share of wealthy households, depends on the relative wealth shares inside of the top wealth percentile. Different growth rates cause this composition to vary over time. In the results that follow, I show that the moderate heterogeneity in growth rates across cohorts results in substantively different conclusions regarding the sources of increasing wealth inequality. This can be seen visually in Figure 8, which plots the cumulative increase in wealth inequality since 1986 as well as the contributions due to incumbent growth and displacement.

In Table 5, I present estimates of wealth growth for ex ante wealthy households. I do this by fixing a population of Forbes 400 households who have appeared on the list prior to a given year  $t$ , and following that population of households through 2018. I refer to these as incumbent growth rates to distinguish from the cohort growth rates discussed earlier. A population of incumbent households as of year  $t$  includes households who entered the Forbes list anywhere between 1982 and year  $t$ , whereas the year  $t$  cohort of households only includes households who first entered the Forbes list within the five years prior to  $t$ . Therefore, the incumbent growth rate is the wealth-weighted average of cohort growth rates.

Using the estimates of incumbent cohort wealth growth, I can decompose the rise in

wealth inequality into a within term and a displacement term. The within term captures the growth rate of already-wealthy individuals, while the displacement term captures the contribution of newly-wealthy individuals replacing previously-wealthy individuals in top wealth percentiles. Table 6 presents data from standard sources on the wealth growth of top wealth, captured by the Forbes 400; aggregate household wealth; and the relative increase in top wealth shares over a period of time. To decompose the component attributable to the within term, I compare aggregate household wealth growth to the wealth growth of households who entered the Forbes 400 in the five years prior to the period of interest. By comparing the Cohort column and the Forbes 400 column, we see that no cohort has outperformed the Forbes 400 as a whole over long periods and that the role of displacement is consistently large. Cohort growth rates are the estimates of the long-term growth rate of the cohort of newly wealthy households, and the results in the table indicate that high growth rates of wealth among newly wealthy households *after entering the Forbes 400* cannot explain the rise in wealth inequality.

In addition to the the population of newly wealthy households, we can also analyze the growth rates of ex-ante wealthy households. Table 7 presents the results of the same decomposition, where incumbent growth rates are used rather than cohort growth rates. Incumbent households are those who were on the Forbes 400 at any point in the 5 years prior to the start of the period. From the consistently high relative contribution of displacement, we see that it is also not the wealth accumulation of ex-ante wealthy households that explains the bulk of the rise in wealth inequality. Both proxies for the within term lead to the conclusion that over 80 percent of the increase in wealth inequality since 1986 is the result of displacement.

With the exception of the 2001 Incumbent Cohort, rising inequality is the result of both a growing incumbent wealth share as well as displacement. The 2001 Incumbent Cohort is the only cohort for which the incumbent wealth share has declined, and this is likely attributable to tech bubble, which led to many one-time appearances on the Forbes 400.

Those households suffered large drops in their wealth and exited the Forbes 400 list, leading to low estimates of the present day wealth of that Incumbent Cohort. The fact that the tech bubble as a industry-specific wealth shock is likely the reason that the 2006 incumbent cohort has grown their wealth share over time despite the Financial Crisis. Timing considerations also play a role. The relative wealth share of the Forbes 400 attained high water marks in the years 2000 and 2008. Thus, the 2006 incumbent cohort's initial wealth estimates do not reflect a fall from this local maximum.

The contribution of displacement has declined over the sample period, from over 80 percent since the late 1980's to just over 50 percent over the last 10 years. My decomposition of the cohort growth rates suggests that life-cycle effects play a role in this relative decline. More recent incumbent populations are earlier in the life cycle, so that their growth rates of wealth are still relatively high.

For comparison, I plot the cumulative contribution of displacement, estimated using one-year incumbent growth rates, in Figures 12 and 13. The chained one year growth rates overestimate the long term wealth growth of wealthy households, and consequently underestimates the contribution of displacement. For the full sample, starting in 1982, the relative contribution of the within and displacement terms are roughly equal, consistent with the results of Gomez (2018). For the sample starting in 1986, the within term calculated using chained one year estimates of incumbent wealth growth outweighs the importance of the displacement term, and explains the bulk of the increase in the wealth share of the Forbes 400.

## 4 Implications for Economic Models

A primary reason for economists to be aware of facts regarding wealth inequality is that many standard economic models make strong predictions about agents' wealth growth. This includes both static models of cross-sectional heterogeneity among agents as well as dynamic

models which explicitly address the evolution of the wealth distribution. By documenting new facts regarding household wealth dynamics, my empirical results serve as informative benchmarks against which to evaluate many economic models. In this section, I discuss several classes of models and their implied moments of wealth inequality. I explain why representative agent models which ignore heterogeneity and market incompleteness produce predictions inconsistent with the data. Finally, I outline a model that can jointly address many of my empirical facts and discuss the implications of the model for asset prices.

**Additional Dimensions of Heterogeneity** A limitation of my methodology is that I cannot identify differences in dispersion across cohorts. By aggregating at the cohort level, idiosyncratic shocks are diversified. While my panel is constructed at the household level, estimating dispersion based on imputed estimates of wealth leads to low statistical power tests of heterogeneous dispersion. At the same time, differences in dispersion are distinct from differences in growth rates and do not affect my decomposition of inequality into the within and displacement terms.

**Models of the Wealth Distribution** The single asset, representative agent model is a work horse model in macro-finance. In this model, agents face inter-temporal investment and savings decisions and trade in time-zero complete markets to hedge future consumption risk. A robust prediction of these models is that post-trade consumption and wealth growth are equalized across all agents. As preferences are typically assumed to be homothetic, there are no wealth effects and aggregate wealth in the economy is a sufficient statistic for the wealth distribution. This means that the representative agent model is consistent with any observed wealth distribution. The challenge for these models is that, after agents trade and equalize wealth growth, the scaled wealth distribution is constant over time. Thus, these models are inconsistent with the rise of wealth inequality. Consistent with the model's prediction of a constant scaled wealth distribution, the models also predict no displacement in the ranks of

top household wealth.<sup>4</sup> A household's rank in the wealth distribution at time  $t$  is identical to their rank in the wealth distribution at time  $t + 1$ . Thus, the model is able to rationalize neither increasing wealth inequality nor the observed level of displacement.

An extension of the representative agent model that is able to rationalize time-varying wealth inequality is the introduction of heterogeneous agents. When differences between agents lead to differences in investment and saving decisions, aggregate wealth is no longer a sufficient statistic for the wealth distribution. In contrast to the representative agent model, in which today's wealthy households are identical to those of yesterday and even yesteryear, the heterogeneous agent model features churn in the wealth distribution. Today's wealthy are a mixture of those who were born wealthy and those who held high growth rate portfolios. Thus, a heterogeneous agent model can rationalize increasing wealth inequality as the result of heterogeneous growth rates of wealth across agents.

The challenge for the heterogeneous agent model is to rationalize relatively low growth rates of wealth for ex-ante wealthy households will also rationalizing increasing wealth inequality. The puzzle is explaining why wealth inequality increases (decreases) over time if wealthy households are those with lower (higher) average growth rates of wealth? In my empirical results, I find that Forbes 400 households have wealth growth rates similar to aggregate household wealth. While these ex-ante wealthy households do outgrow aggregate wealth slightly, the growth of these incumbents can only explain 20 percent of the rise in wealth inequality. The heterogeneous agent model would predict incumbent growth drives changes in wealth inequality.

I find that displacement is responsible for 80 percent of the rise in wealth inequality. Incumbent wealth households have continued growing their wealth, but have been displaced in the top wealth percentile by new households entering. Furthermore, in the data, these households growth rates are not relatively high after entering the top wealth percentile. These facts suggests are consistent with a heterogeneous agent model in which changes in the

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<sup>4</sup>A small amount of displacement can be attributed to death and demography.

distribution of new household wealth, rather than cross-sectional differences in investment and savings decisions, drives increases in wealth inequality.

**Model Selection** The motivation for selecting models on the basis of their ability to simultaneously match wealthy agents' wealth dynamics and the aggregate wealth distribution is that wealthy agents hold a large fraction of the wealth in the economy and are a likely candidate for marginal agents who impact prices. This has two sets of implications useful for selecting asset pricing models. The first is in rationalizing observed prices in financial markets. The second is in rationalizing realized wealth dynamics.

Any arbitrage-free model of asset prices features a stochastic discount factor that correctly prices all traded assets. Equivalently, prices are considered “fair” by all marginal agents in the economy. Thus, observed asset prices should be consistent with the stochastic discount factor of wealthy households.

Furthermore, the wealth dynamics of wealth agents should be interpreted as the equilibrium decisions of a marginal economic agent. Qualitatively, these wealth dynamics do not look like the dynamics of a passive index investor who loads on the market. Wealthy households' wealth dynamics feature idiosyncratic dispersion and heterogeneous growth rates. Models that predict investment behavior inconsistent with observed wealth dynamics are thus likely to be mis-specified.

There is an additional, practical, consideration that makes wealth dynamics a desirable diagnostic tool. For top wealthy households, wealth dynamics are almost identical to returns on their investment portfolio. It is well known that the income distribution features a thinner tail than the wealth distribution. Wealth dynamics for top wealthy households are driven by their portfolios, not their incomes.

**Models of Firm Dynamics and Ownership** What kinds of assets can explain these wealth dynamics? A model featuring concentrated firm ownership is a parsimonious model of wealthy households portfolio holdings that can rationalize the observed wealth dynamics

and also the large role of displacement in the rise of wealth inequality. Increasingly skewed firm size distributions have been discussed in Hartman-Glaser, Lustig, and Xiaolan (2017) and Autor et al. (2017) and offer an explanation for the economic mechanism explaining how new households can accumulate significant wealth in a short period of time. My observed life cycle effects across wealthy cohorts mirror those posed in Luttmer (2007) as an explanation for the observed size distribution of firms. Surviving firms gradually decline in growth rates over time. Persistent firm percentage ownership and a constant dividend-yield are sufficient conditions for firm dynamics to drive wealth dynamics. This is distinct from the model of Kogan, Papanikolaou, and Stoffman (2013), which features a skewed distribution of innovation and displacement. In that model, firms differ in their growth rates, but incumbent investors are diversified and thus there is no cross-sectional heterogeneity in wealth dynamics.

## 5 Conclusion

I present a model relating wealth inequality and asset prices. In the model, the rise in wealth inequality, coupled with the decline in interest rates, points to increased displacement as the primary driver of increasing wealth inequality. This is consistent with my empirical results, in which I find that over 80 percent of the rise in wealth inequality is driven by the entry of new wealthy households displacing incumbents. This speaks to the importance of “new money” in understanding the rapid rise of wealth inequality in the United States. At the same time, I find that the relative importance of displacement is smaller at shorter time horizons. I show that this can be explained by heterogeneous growth rates across cohorts. I find evidence that growth rates differ across cohorts and can be explained by life cycle effects wherein older cohorts’ wealth accumulates at a slower rate than newer cohorts’ wealth.

My findings have significant implications beyond understanding the rise in wealth inequality. Wealthy households are a likely candidate to be marginal in financial markets, and understanding their portfolio decisions and realized wealth dynamics offer a powerful tool

for model selection. I explain that my empirical results cannot be rationalized by standard macro-finance models featuring a representative agent and complete markets. Models incorporating heterogeneous portfolio holdings and idiosyncratic firm dynamics as in Piketty, Saez, and Zucman (2017) are a promising direction. More generally, asset pricing models ought to incorporate the impact of entry of new agents and investment opportunities that cannot be invested in by incumbent agents. Finally, returns and individual wealth dynamics are linked by the portfolio decisions of households. Understanding these dynamics and the portfolio problem faced by wealthy agents are important directions for future research and offers the potential to combine insights from household finance, asset pricing, and macroeconomics.

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## A Transition Dynamics

Starting from a steady state featuring a relatively low level of  $\kappa$ , upon a regime change to a higher level of  $\kappa$ , the interest rate *falls*. The higher value of  $\kappa$  also implies a decrease in the growth rate of incumbent firms  $\mu^L$ . This can be interpreted as a relative increase in the importance of displacement for economic growth. Absent a drop in the interest rate  $r$ , a decrease in  $\mu^L$  reduces the value of all existing firms in the economy. The high-type agents are constrained and unable to consume more, while the low-type agents have now received a negative wealth shock due to the decrease in  $\mu^L$ , which has the effect of reducing their consumption. Thus, the interest rate must drop in order to clear the consumption market. Increased displacement leads to higher wealth inequality and lower interest rates. Symmetrically, an increase in  $\mu^L$  and a decrease in  $\kappa$  leads to *higher* interest rates. When wealth inequality is the result of high rates of return, the interest rate rises to induce the low type agents to continue lending to high type agents.

Aggregate dividends and output are deterministic following the regime change, enabling me to fully characterize the transition path  $\{r_t\}$ . Figure 5 plots the decline in interest rates  $r_t$  following an increase in  $\kappa$  and a decline in  $\mu^L$  that keeps the long-run growth rate of the economy  $g$  constant. Following an increase in  $\kappa$  and a decrease in  $\mu^L$ , the interest rate  $r_t$  experiences an immediate discontinuous drop, following by a protracted smooth decline to the steady interest rate under the new parameters.

All agents in the economy know the future path of interest rates, which implies a time varying price-dividend ratio  $p$  for the low type firms

$$\int_0^\infty \exp \left\{ \int_0^s (r_{t+u} - \mu^L) du \right\} ds$$

This implies a no-arbitrage condition relating the current interest rate and price-dividend

ratio to tomorrow's price dividend ratio

$$dp_t = \left( (r_t - \mu^L) p_t - 1 \right) dt \quad (20)$$

Equation (20) states that the net return on a low type firm is equal to the dividend flow, plus capital gains accrued by virtue of dividend growth, plus capital gains accrued via changes in valuation ratios.

Solving for the transition path is done via a shooting method procedure, which I describe below. The economy begins in steady state with output  $Y_0 = 1$  and a pool of outstanding loans  $L_0$ . A guess of the price-dividend ratio following the regime change,  $p_0$  implies both the wealth of low type agents  $W_0^L$  and the consumption of low type agents under log preferences. The market clearing condition, restated below,

$$\epsilon_t x_t + (\rho + \delta) \frac{W_t^L}{Y_t} = 1$$

implies a consumption-income ratio  $\epsilon_t$  for the high type agents.

Here, I make the assumption that the high type agents remain constrained following the transition path. Intuitively, this will always be the case following an increase in displacement  $\kappa$ , as the motives for smoothing consumption are made stronger by the lower value of  $\mu_L$ . In this situation, the borrowing constraint implies that the consumption ratio is linear in the interest rate  $r_t$

$$\epsilon_t = 1 + \alpha \left( r_t + \lambda - \mu^H \right)$$

and can be solved for  $r_0$ . Thus, the full economy can be characterized at time 0 just after the regime change. I then use Equations (20) and (13) to calculate next period's price-dividend ratio and outstanding loans, respectively. For the appropriate choice of  $p_0$ , this economy converges to the steady state economy under the new regime, and thus the asymptotic interest rate implied by the choice of  $p_0$  must equal the steady state interest rate  $r^{*,\text{new}}$ .

## B Proofs

**Solution to the High Type Agents' Problem** The problem of a constrained agent can be converted into an unconstrained problem by attaching Lagrange multipliers  $\lambda, \xi_t \geq 0$  to obtain

$$\begin{aligned} \mathcal{L} = \mathbb{E} & \left[ \int_0^\tau e^{-\rho t} u(c_t) dt + e^{-\rho\tau} V_L \left( \frac{y_\tau}{r - \mu_L} - \int_0^\tau e^{-r(s-\tau)} (c_s - y_s) ds \right) \right] \\ & + \lambda \mathbb{E} \left[ \alpha y_0 + \int_0^\tau e^{-rs} (y_s - c_s) ds \right] + \mathbb{E} \left[ \int_0^\tau \xi_t \left( \alpha y_0 + \int_0^t e^{-rs} (y_s - c_s) ds \right) dt \right] \end{aligned} \quad (21)$$

I claim that the optimal consumption process takes either the form

$$c_t = \begin{cases} \rho W_t, & t < \tau, \\ (\rho + \delta) W_t, & t \geq \tau \end{cases}$$

in the case that  $\alpha$  is sufficiently large so that the constraint is not binding; or the form

$$c_t = \begin{cases} \epsilon y_t, & t < \tau, \\ (\rho + \delta) W_t, & t \geq \tau \end{cases}$$

in the case that the constraint binds. The agent's wealth  $W_t$  is given by

$$W_t = \int_0^t (y_s - c_s) e^{r(t-s)} ds + \frac{y_t}{r - \mu_L} \left( 1 + \mathbb{I}_{\mu_H}(\mu) \frac{\mu_H - \mu_L}{r + \lambda - \mu_H} \right)$$

and the marginal propensity to consume out of income is given by

$$\epsilon = 1 + \alpha (r + \lambda - \mu_H)$$

It is straightforward to show that the agent, upon decaying to the low growth state, consumes a constant fraction of wealth  $\rho + \delta$ . In the event that  $\alpha$  is sufficiently large that the borrowing

constraint does not bind, log preferences and i.i.d dividend growth imply that the agent will consume fraction  $\rho$  of her wealth, which follows the process

$$dW = \left( y - \rho W + \mu_H P^H(y) + r(W - P^H(y)) \right) dt + \left( P^L(y) - P^H(y) \right) dN.$$

Let  $\{c_t\}$  be the optimal consumption process. If  $c_t$  prescribes that the borrowing constraint is tight until stopping time  $\tau$ , then we have that

$$\alpha y_t = (y_t - c_t) dt + (1 - (r + \lambda) dt) (\alpha (y_t + dy_t))$$

Substituting in the definition of  $dy$  and dropping higher order  $dt$  terms gives

$$\frac{c_t}{y_t} = 1 + \alpha (r + \lambda - \mu_H).$$

It remains to be shown that the optimal  $c_t$  process keeps the agent at the borrowing constraint. The proof that this is optimal proceeds by contradiction. Assume that an agent who follows  $c_t$  expects her borrowing constraint to be slack over some interval of time  $\mathcal{T} = (t', t' + \Delta t)$ . This implies that her Euler equation holds with equality. Under the assumption of log preferences, it must be that both her wealth and consumption growth during period  $\mathcal{T}$  are equal to  $r - \rho$ . Plugging into the dynamic budget constraint gives

$$(r - \rho) W = y - \rho W + rW + (\mu_H - r) P^H(y)$$

This simplifies to

$$rP^H(y) = y + \mu_H P^H(y)$$

which forms a contradiction, given that  $y$  is positive and  $\mu_H > r$ . Thus there are no such intervals  $\mathcal{T}$  and the constraint is binding almost surely. As shown above, under a binding constraint it is optimal to consume  $\epsilon y_t$ , completing the proof.

## C Data Sources

The initial construction of my panel begins with the Forbes 400 data set. Forbes Magazine publishes a list of the wealthiest 400 Americans. The list is compiled by dedicated staff using a mix of public and private information. The first list was compiled in 1982, and has since been updated annually. By starting with Forbes 400 lists, I have a number of repeated observations for the same individual over many years. Perhaps unsurprisingly, the Forbes 400 list exhibits substantial persistence. From 1982 to 2018, Forbes Magazine published 37 lists of the 400 wealthiest Americans. There could be as many as 14,800 unique names published across those lists. However, the actual Forbes 400 lists feature less than 1,600 unique individuals, corresponding to an average attrition rate of just over 10 percentage points per annum. Equivalently, the average tenure on the Forbes 400 list is roughly 10 years. The data collection challenge of this paper is to fill in wealth observations missing in the Forbes 400 lists.

In order to account for dropouts from the Forbes 400, I employ a number of data sources. As these data sources are unfamiliar to the typical reader, I first enumerate the data sets before discussing each at length below. The data to be described are:

1. Forbes Dropoff List: Annual wealth estimates for displaced Forbes 400 members
2. Forbes Billionaire List: Annual wealth estimates for billionaires
3. Family Structures for Forbes 400 members
4. LexisNexis Property Records for family of Forbes 400 members
5. Wealth-X profiles for individuals exceeding \$30 million net worth

**Forbes Dropoff Lists** The first auxiliary data set is Forbes Magazine’s own published list of drop offs, beginning in 2012. For all subsequent Forbes 400 lists, Forbes Magazine reported the wealth of individuals who were removed from the list on the grounds that they

were no longer among the 400 richest Americans. I manually collect these reports from archives of Forbes' website. Starting from the 14,800 observations in the Forbes 400, the published dropoff lists add an additional 175 observations. These observations are useful in that they are relatively simple to collect and match by name. The weaknesses of this data set are that: (i) it only exists since 2012, (ii) it only contains wealth for dropoffs in the year immediately following their exit from the Forbes 400 list, and (iii) it does not report wealth for deceased individuals. For the purposes of estimating long run trends in top wealth shares, such dropoff data is of limited use. Nevertheless, I present it first because it is the "cleanest" measure of wealth for dropoffs. The wealth estimates are compiled by the same Forbes Magazine staff that publish the main Forbes 400 lists, and thus the methodology for estimating the wealth of these individuals is likely to be consistent. The wealth estimates also feature no selection-bias at the one year horizon, in that all surviving dropoffs have their wealth reported.

**Forbes Billionaire Lists** The second auxiliary data set is Forbes Magazine's published list of world-wide billionaires. This list was first compiled in 1996, and continues to this day. The cutoff for inclusion in the Forbes 400, which I infer from the wealth of the lowest-ranked member in each annual list, has exceeded \$1 billion since 2006.<sup>5</sup> Therefore, for many individuals who dropped off the Forbes 400 post-2006, the magazine staff continues to use a similar methodology to estimate their wealth. I scraped the historical Forbes Billionaire lists from archives of Forbes' website. Importantly, individuals who fall off the Forbes 400 list, but who remain billionaires, stay in the Forbes Billionaire data set. This is the case for a number of individuals, and I am able to combine the data sets to get a balanced panel of wealth for these individuals extending through to 2018. It would be impossible to do this using only the Forbes Dropoff data set for the simple reason that the wealth of dropoffs is only reported for a single year.

Another advantage of the Forbes Billionaire list is that it assists me in estimating the

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<sup>5</sup>The one exception was the cutoff of \$950 million in 2009.

wealth of deceased Forbes 400 individuals. Given my focus on long term trends, my unit of analysis, wherever possible, is the family of a Forbes 400 member.<sup>6</sup> For a number of deceased Forbes 400 individuals, a family member continues to remain on the Forbes 400 list. This is the case, for example, for Dagmar Dolby, the widow of Ray Dolby. Even though Ray Dolby passed away in 2013, Dagmar Dolby survives to this day and continues to be on the Forbes 400. In 2012, the year immediately preceding his death, Roy Dolby was estimated to have a net worth of \$2.4 billion. In 2013, the year Dagmar Dolby first appeared on the Forbes 400, her wealth was estimated to be, again, \$2.4 billion. In other cases, a Forbes 400 member has numerous family members who divide up their wealth, but who nonetheless appear on the Forbes 400 list and for whom the *total* wealth is of similar magnitude to the wealth of the single original family member. This is the case for the Cargill sisters, consisting of Alexandra Daitch, Sarah MacMillan, Lucy Stitzer, and Katherine Tanner, who were the four daughters of W. Duncan MacMillan, who died in 2006. While these cases are relatively easy to identify and account for in the Forbes 400, the Forbes Billionaire data set allows me to identify those cases where the surviving family members are found across the two data sets. Roughly 700 additional observations of family unit wealth are obtained by joining together the Forbes 400 and Forbes Billionaire lists.

As I will elaborate upon later, conducting analysis at the family unit can have a drastic impact on conclusions regarding long terms wealth trends. As a simple example, the 2018 Forbes 400 list features 25 individuals who were on the inaugural 1982 Forbes 400 list, and a total of 68 individuals who first entered the ranks of the Forbes 400 prior to 1990. If, instead, one considers the inaugural year of the family unit, these numbers increase substantially. Eighty-two members of the 2018 Forbes 400 are members of families who were on the inaugural 1982 Forbes 400 list, more than three times the previous number. A total of 130 individuals are members of families that first entered the ranks of the Forbes 400 prior to 1990. This is all despite the fact that, across the 1,580 distinct members of the

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<sup>6</sup>Specifically, I include spouses, ex-spouses, children, and step-children.

Forbes 400, there are 1,373 distinct family units. While this is merely a suggestive feature of the data, there are also methodological reasons to conduct analysis at the level of the family unit. For the purpose of understanding long term trends in top wealth shares and top wealth inequality, inter-generational transfers become increasingly important as one extends the time horizon.

**Family Structures for Forbes 400 members** In order to identify family members, I manually collect data on the names and, where possible, age and location of children and spouses of Forbes 400 individuals. Consistent with Bernstein and Swan (2008), I find that the average Forbes 400 individual has three children. The identification of family members of Forbes 400 individuals is a non-trivial task. While, in recent years, Forbes Magazine attempts to report the marital status for each member, along with the number of children they have, this number is often inaccurate. Common reasons are that the number provided is the number of surviving children, or that the number excludes numerous step-children. Taking Forbes Magazines' estimate as a starting point, I hand collect data on the number and the names of children using a variety of internet data sources. For deceased Forbes 400 members, their obituaries often contain information on surviving family members. Even for surviving individuals, or individuals for whom I could not locate an obituary, it is possible to obtain names of family members using obituaries of parents or siblings. In some cases, Forbes 400 members or their spouses have written books and included dedications to their children. This is the case for, among others, Robert and Janice Davidson, as well as David Shaw.<sup>7</sup> More esoteric examples include Pincus Green, whose children jointly wrote a letter to then-president Bill Clinton requesting a presidential pardon for their father. In total, I identified 4,843 children of Forbes 400 members, and found names and other information for 4,578 of those children. A detailed list of sources used in the construction of this data set is available upon request.

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<sup>7</sup>The Davidsons wrote *Genius Denied: How to Stop Wasting Our Brightest Young Minds*. David Shaw's wife Beth Kobliner wrote *Make Your Kid A Money Genius (Even If You're Not): A Parents' Guide for Kids 3 to 23*.

**LexisNexis Property Records** Thus far, the auxiliary sources of wealth information have relied upon wealth estimates produced by Forbes Magazine staff. In order to account for individuals not found in the Forbes data sets, due either to dropping off prior to 2006 or dropping to below \$1 billion in net worth, I make use of the LexisNexis Public Records data set. LexisNexis offers a search interface through which I can observe basic biographical information, along with address history and property records, for a significant proportion of the American population. For property records, the key feature of the data set for this analysis, LexisNexis provides access to property deed records for 3,017 counties in the United States, out of a total possible 3,144. This is a coverage ratio of 96.0 percentage points. For now, I describe the characteristics of the LexisNexis data set and postpone discussion of how I estimate wealth using the data until Section 3.2. For property assessment records, which are filed more regularly, the coverage ratio is even higher, and covers all but three counties. Biographical information provided includes names of likely family members, employment history, and date of birth. All of this information is linked to an encoded version of a Social Security Number, as well as to a unique database identifier, a **LexID**. Starting with the biographical information included in the Forbes 400 lists, I search for individuals in the LexisNexis database based on name, approximate age, and state of residence. From there, I reject potential matches based on employment history and family information. Through this process, I manually link 1,565 Forbes 400 individuals to a unique **LexID**. For the less than 1 percent of Forbes 400 individuals who I am unable to link to a **LexID**, the reason is typically that the individual has no domestic residences. This is the case for, among others, Victor Fung, J Paul Getty Jr, and Tor Peterson. For each of the 1,565 Forbes 400 individuals that I am able to uniquely identify in LexisNexis, I algorithmically download all property deeds and property assessments pertaining to that individual, as well as the names and addresses of all likely family members. For each likely family member, I then algorithmically find the most likely matched **LexID** corresponding to that individual in the LexisNexis database, based on biographical information, and download all property deeds and assessments pertaining

to these potential family members. The Python code I wrote to automate the extraction of information from the LexisNexis database into a format conducive to empirical analysis is available upon request.

I aggregate property records at the family unit, so that all family members' property records are grouped together. The property records contain geographic identifiers for the property in the form of street address, zoning, and parcel number, as well as some information regarding the value of that property. For property deeds, this valuation information consists of a sale value, a transaction date, names for the buyer and seller, as well as mortgage amount. For property assessments, this valuation consists of an assessed value for the stated tax year. I further process the property records data to account for duplicates and potentially mis-labeled records using two methods. First, I exclude non-apartment properties sharing identical GPS coordinates. Second, I exclude any remaining properties which feature substantially similar parcel numbers. For the bulk of my empirical analysis, I restrict attention to residential properties and exclude properties whose land usage indicates commercial zoning. In Section 3.2, I elaborate on the methodology used to produce a panel of wealth estimates using LexisNexis data.

**Wealth-X Profiles** The final non-standard data set that I use to produce my panel consists of Wealth-X profiles on ultra-wealthy individuals, defined here as individuals with net worth exceeding \$30 million as of 2018. The profiles are maintained by dedicated staff employed by Wealth-X, and contain information derived from publicly disclosed transactions, holdings, philanthropy, conspicuous purchases, board memberships, professional and family ties, and other biographical information. I first extract a list of all ultra-wealthy individuals, both foreign and domestic, in the Wealth-X database. Based on this list of individuals, I then collect each profile and extract family details and portfolio holdings. Thus, my data set contains every individual Wealth-X has identified as having a net worth exceeding \$30 million in 2018. For this paper, I principally focus my attention on domestic ultra-wealthy

individuals, and thus discard all individuals with no business or residential addresses within the United States. I then manually match these individuals to Forbes 400 family units based on the hand-collected family structure information.

Wealth-X is a private corporation that maintains profiles on wealth individuals. While the methodology employed by Wealth-X is unlikely to be identical to that employed by Forbes magazine, the wealth estimates are highly correlated on the overlapping sample. For the population of United States billionaires, Wealth-X's reported list of billionaires slightly exceeds that of Forbes for the year 2018.<sup>8</sup> For the population of ultra-wealthy individuals with net worths exceeding \$30 million, Wealth X reports roughly 20,000 such individuals in the United States for the year 2018. For comparison, the Survey of Consumer Finances estimated that 50,000 ultra-wealthy households, and 640 billionaire households existed in 2016. This is consistent with the characterization that Wealth-X has relatively comprehensive coverage of individuals with net worths as low as \$100 million (a population numbering roughly 7,000), and a random sample of net worths between \$30 million and \$100 million, covering approximately 30 percent of that population.

One limitation of the Wealth-X database is that the portfolio holdings and valuation are as of 2018. Thus, Wealth-X data can only be used to fill in 2018 wealth levels for Forbes 400 individuals. For this reason, I use Wealth-X as a robustness check for both my hand-collected family structure data, as well as my 2018 wealth estimates for Forbes 400 dropoffs. When comparing family structure data, my dataset contains a superset of family members enumerated in Wealth-X. When comparing 2018 wealth estimates between the Forbes 400 list, my 2018 wealth panel, and Wealth-X profile estimates, I find that the estimates are highly correlated at the individual level ( $\rho = 0.8$ ) and similar in terms of implications for aggregate quantities.

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<sup>8</sup>I attribute these discrepancies to differences in methodology and within-calendar year changes in individuals' net worth.

## D Housing Imputation

I assume that household preferences for Forbes 400 families are of the form

$$V_{it} = \log \left( C_{it}^{\psi_i} H_{it}^{\phi_i} \right) + \mathbb{E}_{it} \left[ e^{-\rho_i} V_{i,t+1} \right],$$

where  $C_{it}$  denotes non-housing consumption,  $H$  denotes housing consumption, and  $\rho$  captures the subjective discount of household  $i$ . Under these assumptions, the household myopically consumes a constant proportion  $\rho$  of their wealth, of which a fraction  $\phi_i / (\psi_i + \phi_i)$  consists of expenditures on housing. Abstracting from cross-sectional heterogeneity in financing, I further assume that housing consumption is simply the product of a common rental rate on housing  $p^H$  and the value of the household's residential housing stock.<sup>9</sup> Therefore, housing consumption and period wealth are related by

$$W_{it} = \frac{1}{\rho_i} \frac{\psi_i + \phi_i}{\phi_i} \frac{H_{it}}{p^H}.$$

Under this framework, the fraction of total wealth held in housing is constant over time for each household, and it is possible to use a subset of contemporaneous observations of housing value and total wealth to estimate unobserved total wealth from annual observations of housing wealth.

My imputation procedure based on housing values has a number of advantages. First, as discussing the Data Section, I observe portfolios of real estate for a significant fraction of Forbes 400 households, and thus the method is broadly applicable across the population of interest without need for individual- or family-specific adjustments. Second, the wealth estimates are timely and likely reflect household's current level of wealth. There is significant turnover in real estate portfolios, as Forbes 400 households buy and sell properties often. I

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<sup>9</sup>In general, households in my sample employ little leverage in their home purchases. Among potential explanations, I am most sympathetic to the idea that these households self-finance so as to avoid paying spreads to financial intermediaries.

observe transaction values for these properties, and am able to exclude transactions between related parties using both the buyer and seller names, linking to the family structure data I collected, as well as transaction-level identifiers for intra-family transfers provided by the LexisNexis data set. Thus, my estimates of housing value are market-transaction based, addressing concerns that my estimates of wealth growth are reflecting passive capital gains on a static housing portfolio. Finally, the wealth estimates are based on changes in housing portfolios, rather than levels. I do not require that all households have the same preference parameters  $\psi_i$ ,  $\phi_i$ , and  $\rho_i$ . My identifying assumption is that the proportion of housing to total wealth at the household level remain constant over time. In Appendix E, I discuss another advantage of this specification: robustness to potential household-level heterogeneity in the use of shell corporations to obfuscate home ownership.

A weakness of my method of imputing wealth from the observed real estate panel is that I am assuming a time-invariant relationship between wealth and real estate. While this is a quantitatively reasonable assumption in aggregated data, it abstracts from the underlying portfolio problem faced by the household. In particular, my results cannot speak to rate at which households adjust their real estate holdings in response to changing net worth. A hypothetical process in which a random fraction of households adjust their holdings each year, analogous to a Calvo model of prices, would produce identical results in aggregate real estate holdings. In my panel, this assumption manifests in that my estimates of the wealth of Forbes 400 dropoffs is typically too high at the one year horizon when compared to the available estimates published in Forbes, as dropoff households do not all adjust their real estate values immediately upon falling off the Forbes 400 list. This is one reason that I focus on relatively large cohorts of households and compute growth rates at long horizons.

## E Robustness

**Identifying Wealthy Households** My estimated growth rates are based on a panel of ex-ante wealthy individuals. For the purposes of decomposing the growth of the top wealth share into the contribution of incumbents and entrants, it is not essential that incumbents are defined as the 400 richest households. The empirical strategy is to identify a population of ex-ante wealthy households and estimate the dynamics of their wealth. The advantage of using Forbes is that they are considered to be the *wealthiest* households, and the relative wealth of biographical information about these families enables me to match Forbes 400 households to real estate holdings via the LexisNexis data set. The specific choice to focus on increases in the Forbes 400 wealth share as opposed to other measures of top wealth inequality is innocuous. Figure 15 plots my series for the cumulative increase in the Forbes 400 wealth share against the estimates of the Top 0.01% wealth share from Piketty, Saez, and Zucman (2017). The two measures are very similar and have virtually identical implications for the long term increase in wealth inequality.

**Validating Wealth Estimates** Both the construction of my panel and the bulk of my empirical results rely heavily upon the estimates of wealth published by Forbes Magazine. Over the sample period, the rise in total Forbes 400 wealth has been consistent with the rise in the wealth share of the top 0.01% of households. This serves as validation for the implications drawn from Forbes estimates regarding relative wealth shares and wealth inequality. However, this does not address the potential for individual-level measurement error in Forbes Magazine's wealth estimates. While I cannot validate historical individual wealth estimates published by Forbes, I am able to compare contemporaneous wealth estimates published by Forbes Magazine and Wealth-X. As seen in Figure 14, there is a high level of agreement between the estimates produced by Forbes Magazine and those produced by Wealth-X. Regressing one source of wealth estimates on the other produces both a high R-squared of 0.64, corresponding to a pairwise correlation of 0.8, and an unbiased coefficient close to one.

**Intra-year Wealth Estimates** Forbes Magazines publishes the Forbes 400 list and Forbes Billionaire lists each year, but releases these lists at different points in the year. The Forbes 400 list is typically published in the fall, while the Forbes Billionaire list is published in the spring. The wealth estimates from those data sets are current as of publication, and the discrepancy in publication timings can potentially introduce issues when joining together the data sets into a single, larger panel. The Forbes Dropoff lists, available post-2011, are published alongside the Forbes 400 list in the fall. Wherever possible, I defer to Forbes Dropoff list wealth estimates over Forbes Billionaire list estimates in the same calendar year. The real estate value estimates from LexisNexis are not tied to a given month, and likely correspond to the transaction or assessment date, depending on the exact source of the valuation.

Given my focus on long-run growth rates, these small intra-year timing differences are not instrumental to my results, and so I largely ignore timing discrepancies when joining the various data sets. In an effort to make the market-residualized wealth estimates as accurate as possible, I use July through June market factor returns in my empirical analysis. This is another motivation for using year fixed effects, rather than directly including the market factor, in several of my empirical specifications.

**Imputation of Household Wealth** In the construction of my panel, I use households' real estate holdings to impute wealth observations. In my primary specification, I assume a unit elasticity between housing wealth and total wealth. This is equivalent to a constant portfolio share of residential housing. In Table [INCOMPLETE], I present regression evidence that is consistent with the assumption of unit elasticity. For each cohort, I regress total real estate holdings of surviving cohort members against total wealth of surviving cohort members, where surviving members are defined as those who still appear on the Forbes 400 list. Because housing portfolios are persistent, I run the regression in first differences. The coefficient of the regression is economically close to one at the one, two, five, and ten

year horizons. Furthermore, I find that the explanatory power of the regressions increases with horizon. The increased explanatory power at longer horizons can be explained by short-run adjustment costs in household portfolios. Results are quantitatively similar when I re-estimate my growth rates using the empirical elasticity, rather than my assumption of a unit elasticity.

I also investigate the sensitivity of my results to different ways of measuring real estate value. In my primary specification, I use the most recent purchase or sale price associated with the property. Where no deed transfer data is available, I rely on annual property value assessments. In the latter case, for years in which no property assessment is reported, I use the most recent property value assessment. Results are quantitatively unchanged when I inflate / deflate real estate values using five-digit zip code specific House Price Indices.

**Measurement of Aggregate Wealth** The estimates presented compute growth of aggregate wealth using the net worth of U.S. households. This corresponds to item 35 in Table B.1 of the Financial Accounts of the United States. This series differs from U.S. net wealth presented in line 1 of Table B.1 despite capturing the same conceptual quantity, aggregate wealth. As discussed in Holmquist and McIntosh (2015), the discrepancy between the series arises due to differences in the treatment of government non-financial assets, such as defined benefit pension plan entitlements. Because U.S. net wealth ignores these non-financial assets, it produces a downwards biased estimate of aggregate wealth. As of the fourth quarter of 2018, Household net wealth is roughly 12 percentage points greater than U.S. net wealth. However, the discrepancy between the two series was less than 1 percentage point at the start of the sample period, reflecting the increasing importance of non-financial assets in the calculation of aggregate wealth. As the total wealth of the Forbes 400 is measured independently of the Federal Reserve's estimates of aggregate wealth, using an increasingly downwards biased estimate of aggregate wealth would overstate the rise in wealth inequality over the sample period. For both these reasons, I present results calculated using Household

net worth as the measure of aggregate wealth. At long horizons, this results in an estimate of the annual growth rate of aggregate wealth of 5.7 percentage points compared to a growth rate of 5.3 percentage points when using U.S. net wealth. The choice of measure for aggregate wealth does not drive my results, either qualitatively or quantitatively. Taking the estimate of 5.3 percentage points as the estimate of the annual growth rate of average wealth leads to me to attribute 75 percent of the increase in top wealth inequality to displacement compared to my preferred estimate of 82 percent.

**Properties held in Tax Shelters** It is certainly true that wealthy households do not hold all their real estate under their own name. The most convincing evidence for this is the fact that I do *not* observe property ownership for every Forbes 400 family. At the same time, I can reasonably assume that virtually every Forbes 400 family owns at least one home. One source of these omissions is that these homes may be owned by limited liability corporations. A case in which I can verify this is Mark Zuckerberg, the founder of Facebook. His primary address is reported in numerous articles online, and I am able to link him to this primary address in LexisNexis' data set. What is missing from LexisNexis, and from my data set, is proof that he owns this property. The deeds for this property are linked to an limited liability corporation which cannot be linked back to Mr. Zuckerberg, and thus I do not observe his housing portfolio. This can be modeled as the following

$$H_{it} = \kappa_i H_{it}^*$$

For a given household  $i$ , I observe fraction  $\kappa$  of their total house value  $H^*$  in LexisNexis. For a small proportion of households, such as that of Mr. Zuckerberg,  $\kappa = 0$ , and thus I cannot estimate his total wealth using my methodology. However, given that I do observe some housing, corresponding to the case that  $\kappa > 0$ , my methodology is unbiased so long as  $\kappa$  remains constant over time at the household level. In imputing these observations, I am assuming that households do not engage in increased usage of obfuscatory methods as a

function of wealth, cohort age, or time.

# Figures

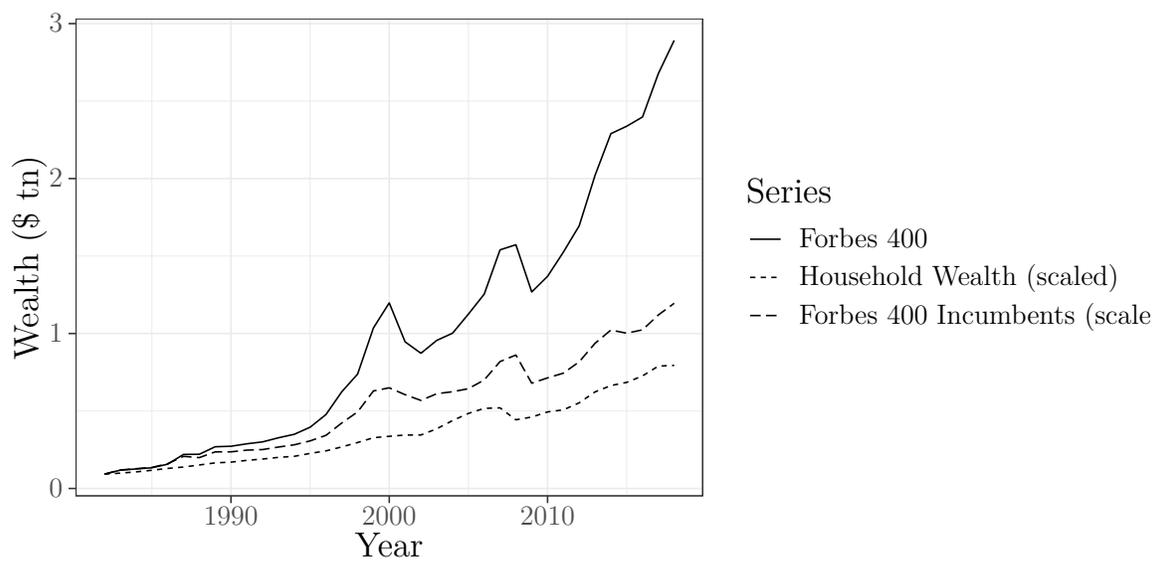


Figure 1: Comparison of Wealth Growth, 1982 - 2018. The total nominal wealth held by all members of the Forbes 400 is plotted in solid black. Aggregate household wealth, scaled to match the total Forbes wealth in 1982, is plotted in short dashes. The total nominal wealth held by incumbent Forbes 400 members, scaled to match the total Forbes wealth in 1982, is plotted in long dashes.

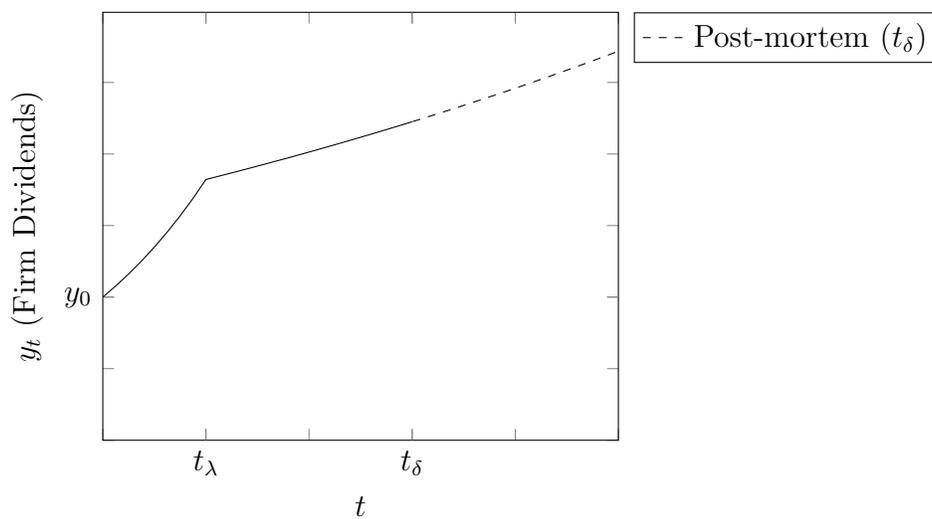


Figure 2: Illustrative Firm Dynamics. The figure plots a representative draw of dividends  $y_t$  for a firm owned by an agent born at time  $t = 0$ . At time  $t_\lambda$ , the firm transitions to the low growth state. At time  $t_\delta$ , the owner dies. It is important to note that the firm continues to produce output and grow at rate  $\mu^L$  after the owner passes away.

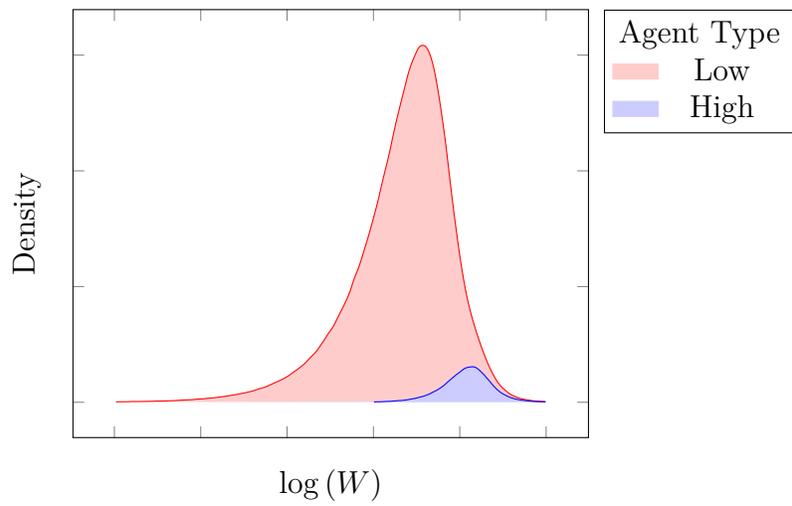


Figure 3: Stationary Wealth Distribution. New agents are born with wealth drawn from an exponential distribution with scale parameter  $\kappa$ .

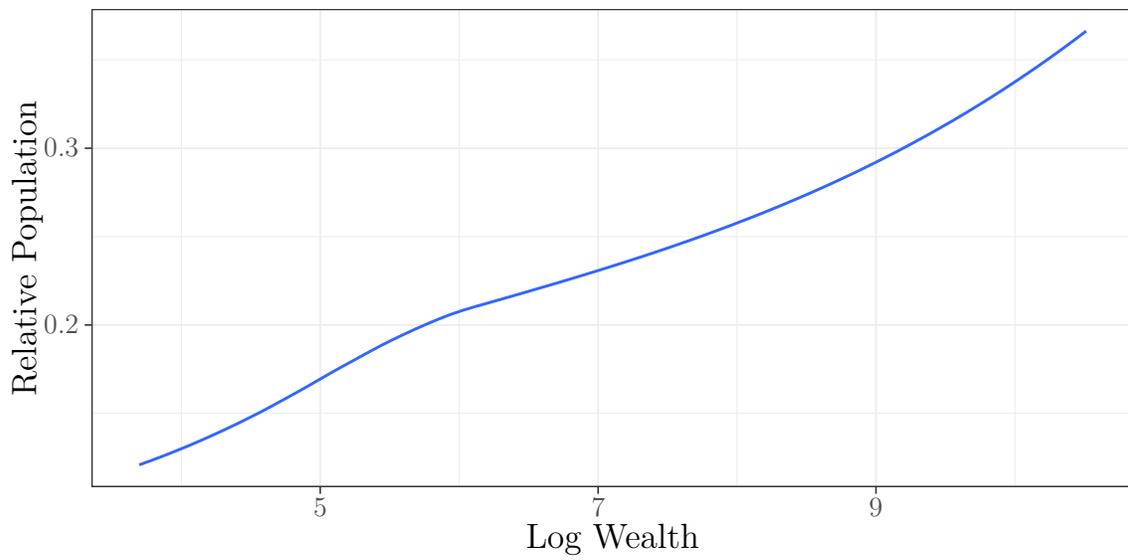


Figure 4: Fraction of High Type Agents. The figure plots the fraction of high type agents among the population of agents with wealth greater than cutoff  $q$ . Agents in the upper percentiles of the wealth distribution are more likely to be in the high growth state.

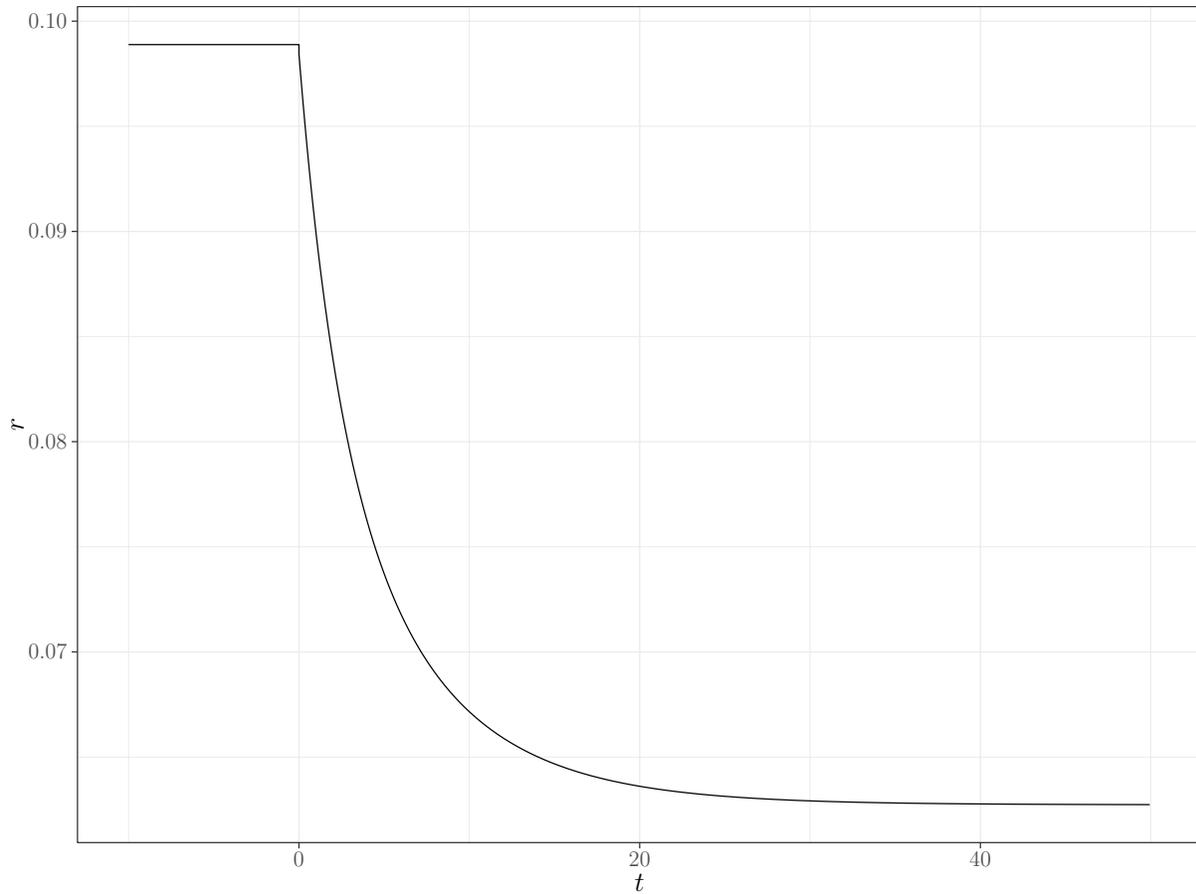


Figure 5: Transition path of interest rates. Prior to time  $t = 0$ , the economy is in steady-state. Following an increase in  $\kappa$  and a decrease in  $\mu_L$ , the interest rate  $r_t$  experiences an immediate discontinuous drop, following by a protracted smooth decline to the steady interest rate under the new parameters.

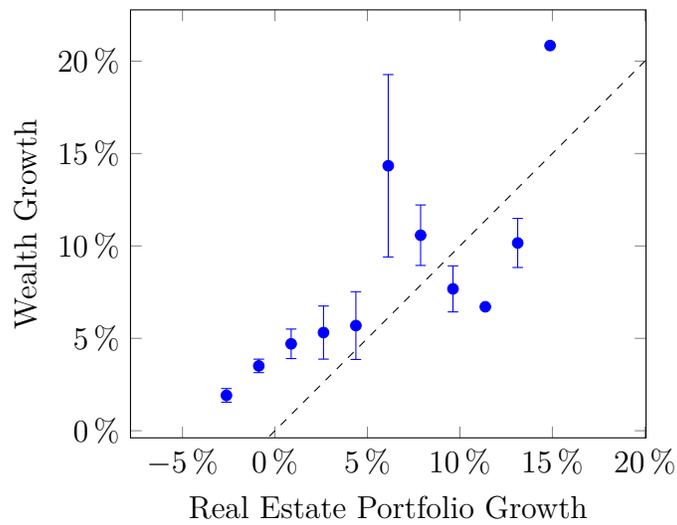


Figure 6: Real Estate Portfolio Growth and Total Wealth Growth, 5-Year Horizon. For individuals who remained on the Forbes 400 list, I plot the annualized growth rate of real estate portfolio growth, obtained from LexisNexis, against the annualized growth rate of wealth, obtained from Forbes 400 lists.

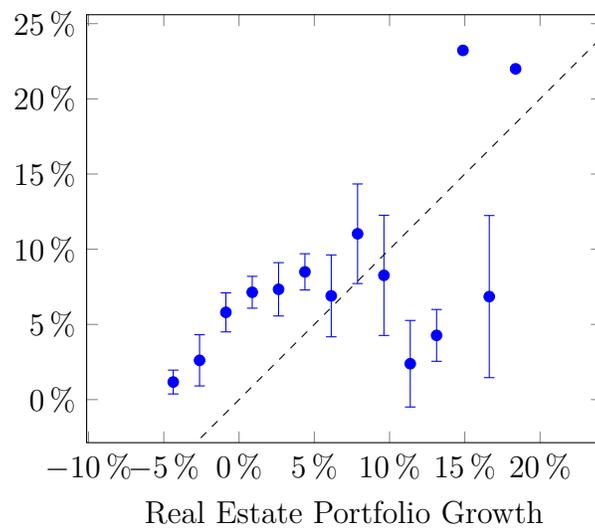


Figure 7: Real Estate Portfolio Growth and Total Wealth Growth, 10-Year Horizon. For individuals who remained on the Forbes 400 list, I plot the annualized growth rate of real estate portfolio growth, obtained from LexisNexis, against the annualized growth rate of wealth, obtained from Forbes 400 lists.

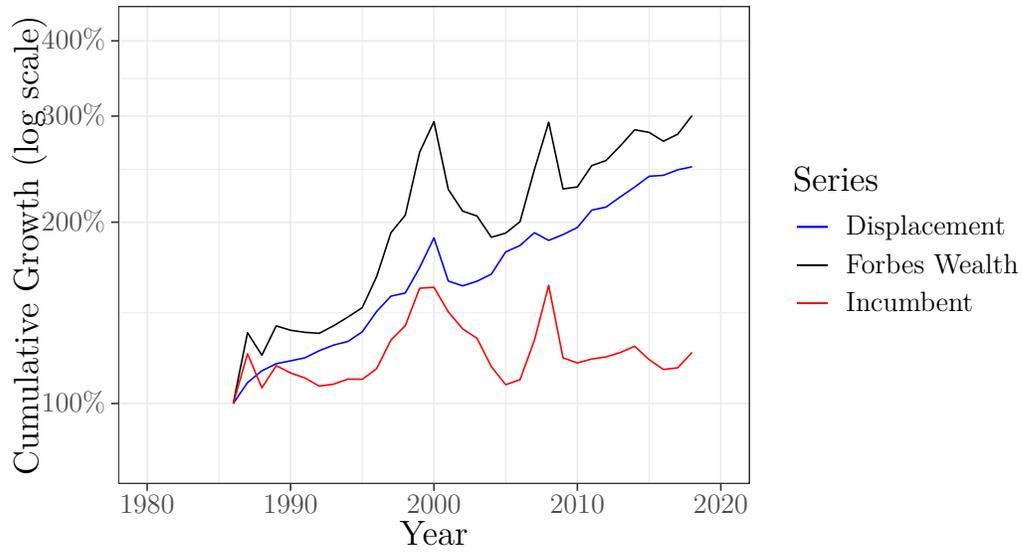


Figure 8: Decomposition of Wealth Inequality, 1986–2018. I plot the cumulative wealth growth of the 1986 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

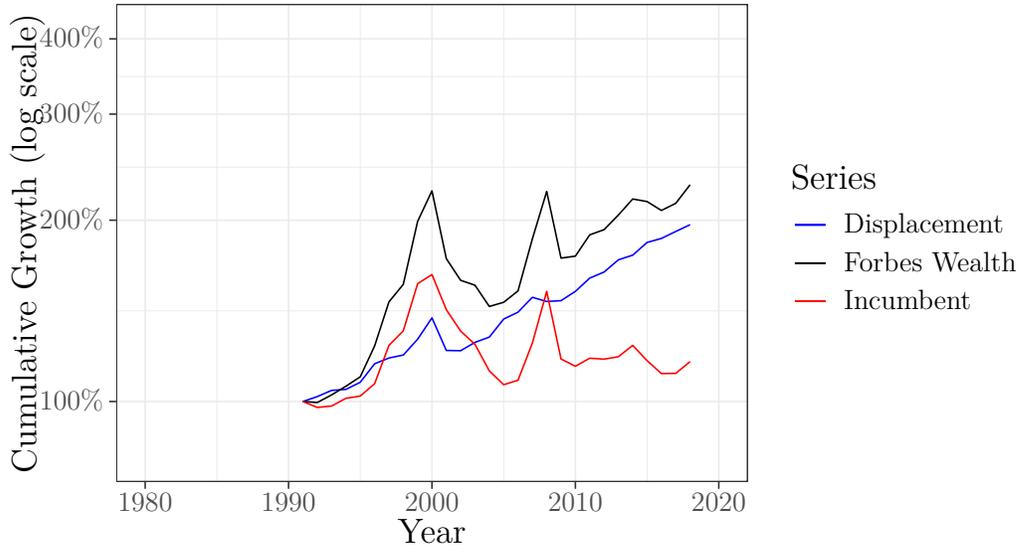


Figure 9: Decomposition of Wealth Inequality, 1991–2018. I plot the cumulative wealth growth of the 1991 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

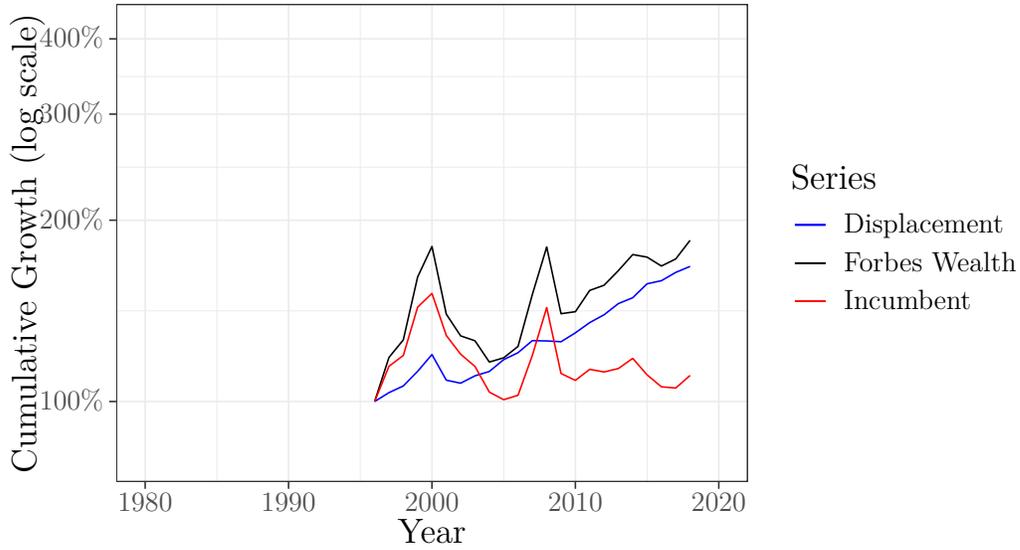


Figure 10: Decomposition of Wealth Inequality, 1996–2018. I plot the cumulative wealth growth of the 1996 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

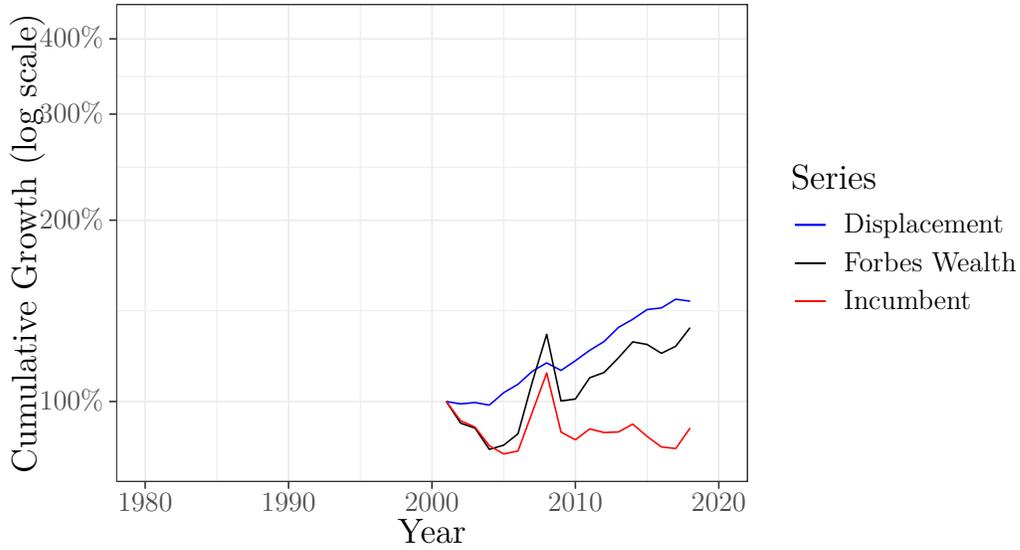


Figure 11: Decomposition of Wealth Inequality, 2001–2018. I plot the cumulative wealth growth of the 2001 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

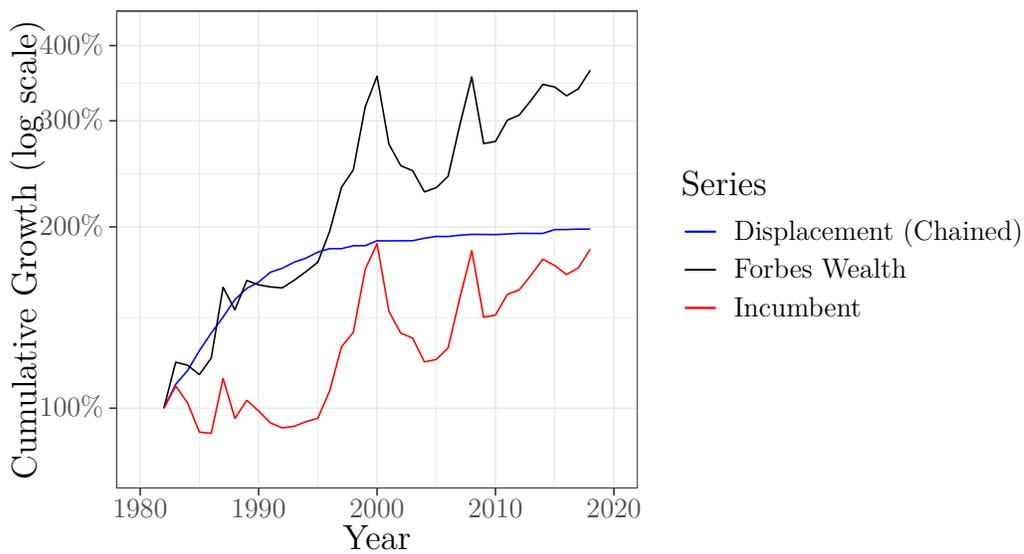


Figure 12: Decomposition of Wealth Inequality, 1982–2018. I plot the chained one year estimates of each Incumbent Cohort (Red). I plot the cumulative wealth growth of the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

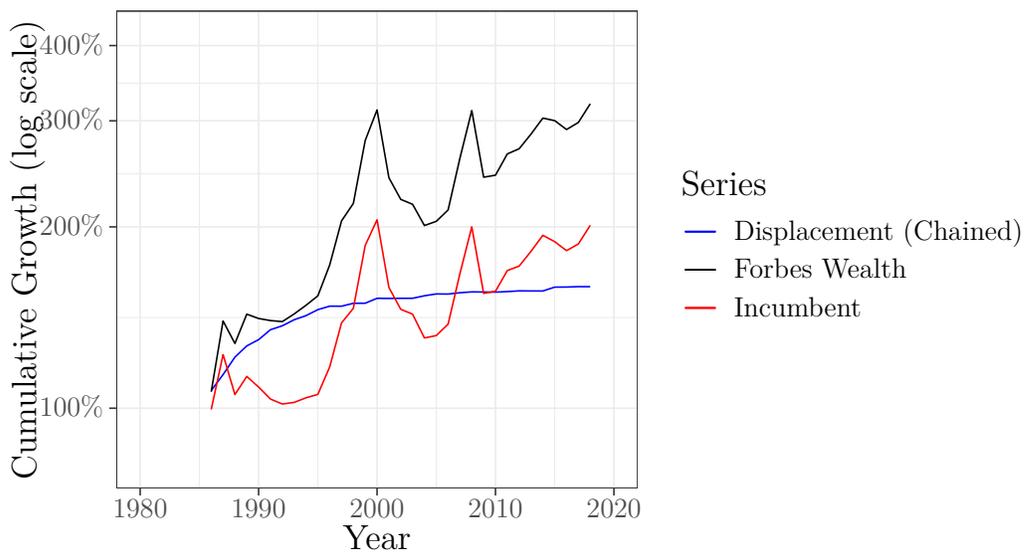


Figure 13: Decomposition of Wealth Inequality, 1986–2018. I plot the chained one year estimates of each Incumbent Cohort (Red). I plot the cumulative wealth growth of the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

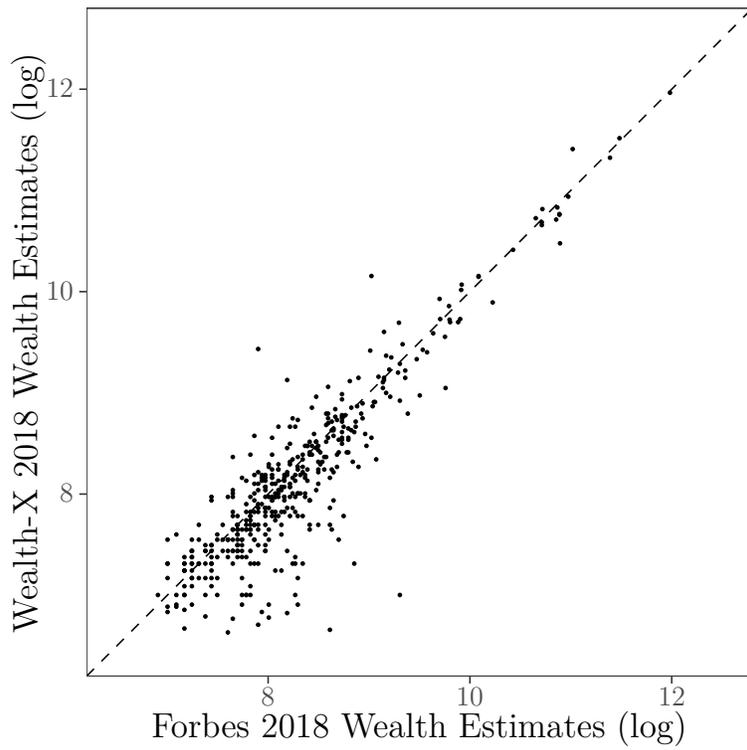


Figure 14: Plot of 2018 estimates of wealth from Forbes Magazine (x-axis) and Wealth-X (y-axis) for matched individuals, in logs.

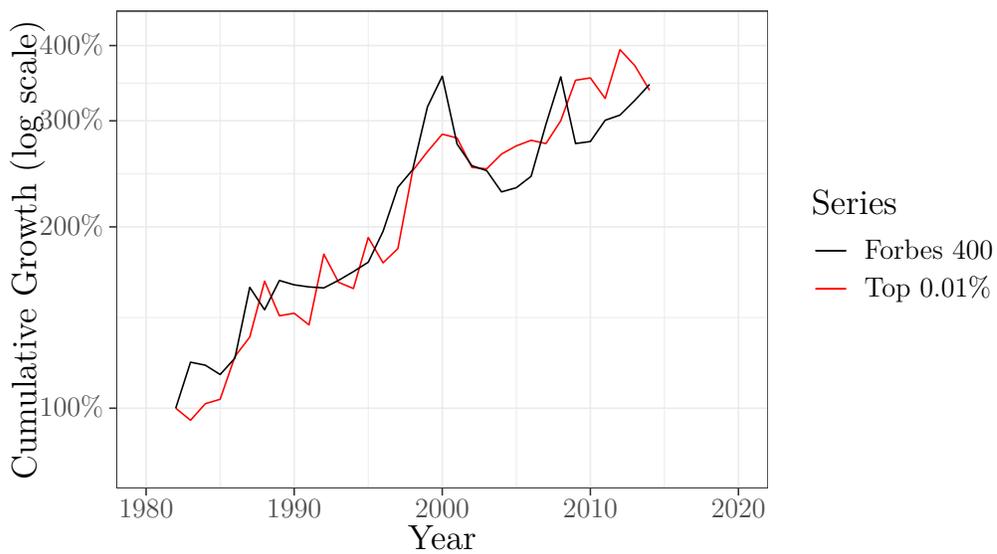


Figure 15: Two measures of Top Wealth Inequality, 1982–2014. I plot the cumulative growth rate of the Forbes 400 (Black) and Top 0.01% (Red) Wealth Shares. The Forbes 400 Wealth Share is calculated from the Forbes 400 lists published by Forbes Magazine and is available since 1982. The Top Wealth Share data is from Piketty, Saez, and Zucman (2017) and is available through 2014.

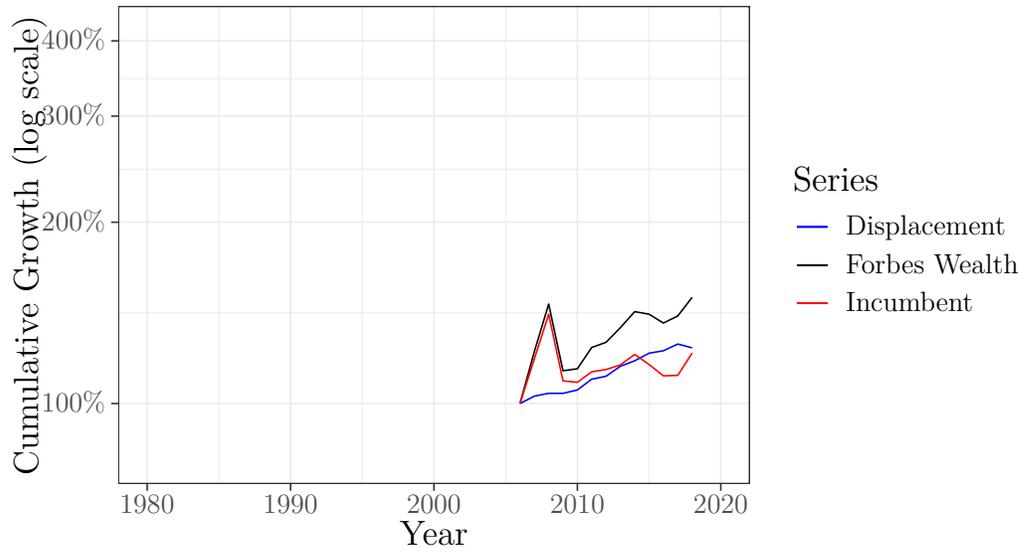


Figure 16: Decomposition of Wealth Inequality, 2006–2018. I plot the cumulative wealth growth of the 2006 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

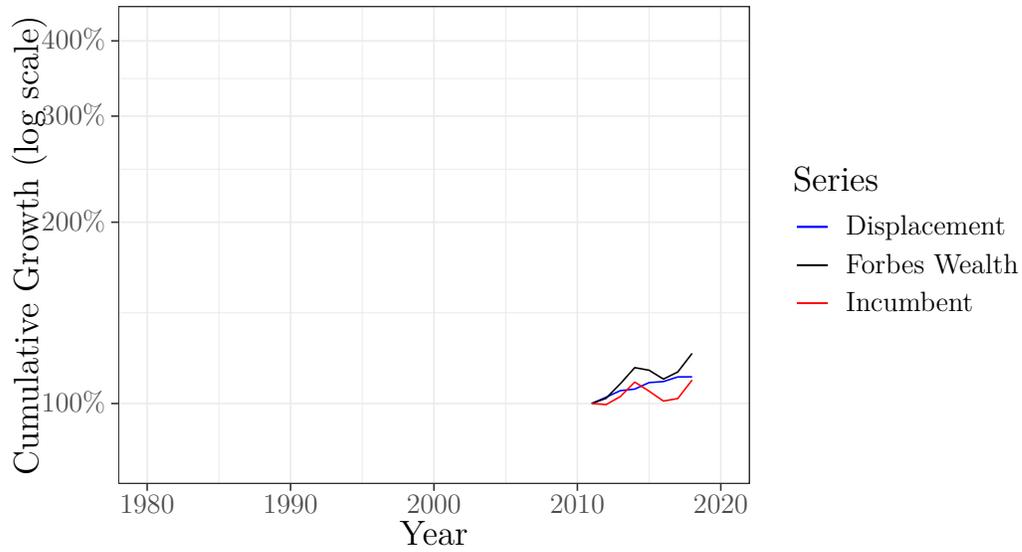


Figure 17: Decomposition of Wealth Inequality, 2011–2018. I plot the cumulative wealth growth of the 2011 Incumbent Cohort (Red), the Forbes 400 (Black), and the implied contribution of Displacement (Blue). Growth rates of incumbent cohort wealth and top wealth are deflated by the growth of aggregate wealth and should be interpreted as growth rates of incumbent cohort and top wealth shares.

## Tables

Cohort	Size	Forbes	Augmented Forbes	Imputed Panel
1982–1986	552	61	71	163
1987–1991	159	30	39	75
1992–1996	145	35	46	94
1997–2001	181	43	52	125
2001–2006	107	40	51	92
2006–2011	112	57	83	106
2011–2016	88	56	76	85
2017–2018(*)	28	28	28	28

Table 1: Summary statistics for Entry Cohorts. Entry Cohorts are defined based on the first year the family is observed in the Forbes 400. The total number of the individuals in the cohort is listed under Size. The number of cohort members with wealth estimates in the 2018 Forbes 400 list is presented under Forbes. The number of cohort members with wealth estimates in some Forbes Magazine publication is presented under Augmented Forbes. The number of cohort members with estimates in my panel is presented under Imputed Panel. Due to its small relative size, I exclude the 2017-2018 Forbes 400 cohort in my empirical analysis.

Period	Entry Cohort					
	1986	1991	1996	2001	2006	2011
1986–1991	8.7 %					
1991–1996	6.5 %	10.3 %				
1996–2001	11.4 %	16.6 %	10.0 %			
2001–2006	2.9 %	2.1 %	7.6 %	7.5 %		
2006–2011	1.2 %	1.5 %	2.5 %	-0.4 %	3.3 %	
2011–2016	6.4 %	4.8 %	6.0 %	5.3 %	8.6 %	8.3 %
2016–2018	7.7 %	3.3 %	6.3 %	13.0 %	8.6 %	6.0 %
Whole Sample	6.3 %	6.8 %	6.6 %	5.2 %	6.4 %	7.7 %

Table 2: Period Growth rates, by Entry Cohort. Annualized wealth growth rates of different Entry Cohorts of the Forbes 400, measured across five-year periods. Entry Cohorts are as defined in the text. Whole Sample growth rates are annualized wealth growth rates of wealth from the first year of the Cohort to 2018.

Cohort	Wealth Growth			
	(1)	(2)	(3)	(4)
1982–1986	6.3 %	1.9 %	1.9 %	0.0 %
1987–1991	6.8 %	1.9 %	2.5 %	1.0 %
1992–1996	6.5 %	2.3 %	2.7 %	1.2 %
1997–2001	5.2 %	2.5 %	1.8 %	1.8 %
2002–2006	6.4 %	2.3 %	2.4 %	3.2 %
2006–2011	7.6 %	1.5 %	2.4 %	2.4 %
<i>New – Old</i>	1.4 %	-0.3 %	0.5 %	2.4 %
Mkt	N	N	Y	N
Year F.E	N	Y	N	Y
N	126	28	28	126

Table 3: Decomposition of Entry Cohort Growth Rates. I decompose annualized entry cohort growth rates into common time-varying components and cohort-specific, time-invariant components. Column (1) reports realized growth rates for each entry cohort. Column (2) reports entry cohort growth rates, controlling for five-year binned fixed effects, Column (3) reports the residual growth rates after projecting entry cohort growth rates onto Market returns. Column (4) reports residual entry cohort growth rates, controlling for single year fixed effects.

	(1)	(2)	(3)	(4)
Age	-0.2 %**		-0.2 %**	
$I_{(1, 5]}(\text{Age})$		0.7 %		0.0 %
$I_{(6, 10]}(\text{Age})$		0.6 %		-0.2 %
$I_{(11, 15]}(\text{Age})$		0.4 %		-0.5 %
$I_{(16, 20]}(\text{Age})$		0.4 %		-0.5 %
$I_{(21, 25]}(\text{Age})$		0.0 %*		-1.0 %*
$I_{(26, 30]}(\text{Age})$		-0.2 %*		-1.1 %*
$I_{(31, 35]}(\text{Age})$		0.2 %		-0.8 %
Cohort F.E	N	N	Y	Y
Mkt	Y	Y	Y	Y
N	28	28	28	28

\*\*  $p < 0.05$ , \*  $p < 0.10$

Table 4: Decomposition of Entry Cohort Growth Rates. I decompose entry cohort growth rates into common time-varying components, cohort-specific, time-invariant components, and common, cohort age dependent components. Column (1) reports the effect on age, controlling for contemporaneous market returns. Column (2) reports effects of age, estimated non-parametrically using a series of age buckets. Column (3) reports the age coefficient, controlling for cohort effects and market returns. Column (4) reports the same non-parametric estimates as in Column (2), where I additionally control for cohort-specific effects.

Period	Incumbent Cohort					
	1986	1991	1996	2001	2006	2011
1986–1991	8.7 %					
1991–1996	6.5 %	7.2 %				
1996–2001	11.4 %	12.7 %	12.1 %			
2001–2006	2.9 %	2.7 %	3.5 %	4.3 %		
2006–2011	1.2 %	1.3 %	1.6 %	1.3 %	2.1 %	
2011–2016	6.4 %	6.0 %	5.8 %	5.8 %	6.9 %	7.4 %
2016–2018	7.7 %	6.7 %	6.6 %	8.1 %	8.8 %	8.5 %
Whole Sample	6.3 %	6.0 %	5.8 %	4.3 %	5.2 %	7.7 %

Table 5: Period Growth rates, by Incumbent Cohort. Annualized wealth growth rates of different Incumbent Cohorts of the Forbes 400, measured across five-year periods. Incumbent Cohorts are as defined in the text. Whole Sample growth rates are annualized wealth growth rates of wealth from the first year of the Cohort to 2018.

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Period	Long-Run Growth Rates				Relative Contribution	
	Forbes 400	Cohort	Household	Inequality	Entry Cohort	Displacement
1986–2018	9.1 %	6.3 %	5.7 %	3.4 %	18 %	82 %
1991–2018	8.5 %	6.8 %	5.5 %	3.1 %	43 %	57 %
1996–2018	8.2 %	6.6 %	5.4 %	2.8 %	41 %	59 %
2001–2018	6.6 %	5.2 %	4.9 %	1.7 %	16 %	84 %
2006–2018	7.0 %	6.4 %	3.6 %	3.4 %	82 %	18 %
2011–2018	9.1 %	7.7 %	6.4 %	2.7 %	45 %	55 %

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Table 6: Decomposition of Wealth Inequality, by Entry Cohort. For five year staggered periods, I present annualized growth rates of the Forbes 400, the most recent Entry Cohort as of the start of the Period, and Aggregate household wealth. The difference between the growth rates of the Forbes 400 and Aggregate household wealth is the increase in Inequality. The relative contributions to wealth inequality of the Entry Cohort and of Displacement are presented in the last two columns. Entry Cohort is calculated as  $(\text{Cohort} - \text{Household}) / (\text{Forbes 400} - \text{Household})^{-1}$

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Period	Long-Run Growth Rates				Relative Contribution	
	Forbes 400	Incumbent	Household	Inequality	Incum. Cohort	Disp.
1986–2018	9.1 %	6.3 %	5.7 %	3.4 %	18 %	82 %
1991–2018	8.5 %	6.0 %	5.5 %	3.1 %	18 %	82 %
1996–2018	8.2 %	5.8 %	5.4 %	2.8 %	16 %	84 %
2001–2018	6.6 %	4.3 %	4.9 %	1.7 %	-36 %	136 %
2006–2018	7.0 %	5.2 %	3.6 %	3.4 %	48 %	52 %
2011–2018	9.1 %	7.7 %	6.4 %	2.7 %	47 %	53 %

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Table 7: Decomposition of Wealth Inequality, by Incumbent Cohort. For five year staggered periods, I present annualized growth rates of the Forbes 400, the most recent Incumbent Cohort as of the start of the Period, and Aggregate household wealth. The difference between the growth rates of the Forbes 400 and Aggregate household wealth is the increase in Inequality. The relative contributions to wealth inequality of the Incumbent Cohort and of Displacement are presented in the last two columns. Incum. Cohort is calculated as  $(\text{Incumbent} - \text{Household}) / (\text{Forbes 400} - \text{Household})^{-1}$