Investor Sophistication and Capital Income Inequality[*]

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Abstract

Capital income inequality is large and growing fast, accounting for a significant portion of total income inequality. We study its growth in a general equilibrium portfolio choice model with endogenous information acquisition and heterogeneity across household sophistication and asset riskiness. The model implies capital income inequality that grows with aggregate information technology. Investors differentially adjust both the size and composition of their portfolios, as unsophisticated investors retrench from trading risky securities and shift their portfolios toward safer assets. Technological progress also reduces aggregate returns and increases the volume of transactions, features that are consistent with recent U.S. data.

1 Introduction

The rise in income and wealth inequality has been among the most hotly discussed topics in academic and policy circles.[1] Among the possible explanations, heterogeneity in the returns on savings—due to differences in rates of return or in the composition of the risky portfolio—has been highlighted as an important driver. This factor has emerged in empirical work on the wealth distribution, such as Fagereng, Guiso, Malacrino & Pistaferri (2016a; 2016b) and in research focused on the very top of the wealth distribution (Benhabib, Bisin & Zhu, 2011).[2] However, as noted by De Nardi & Fella (2017), more work is needed to understand the determinants of such heterogeneity.

This paper studies capital income inequality growth in a portfolio choice model with information constraints. When investors differ in their capacity to process news about risky asset payoffs, both the size and the composition of the risky portfolios differ across investors. Not surprisingly, this generates inequality. More interestingly, progress in the aggregate information processing technology can exacerbate this inequality, and this effect can be economically large, as less sophisticated investors get priced out of high-return assets. This pecuniary externality arises even in a setting with a single risky asset, but is amplified in an economy with heterogeneous assets.

At the core of our model is each investor's decision of how much to invest in assets with different risk characteristics. This decision is shaped by the investors' capacity to pro-

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[1]See Piketty & Saez (2003); Atkinson, Piketty & Saez (2011). A comprehensive discussion is also offered in the 2013 Summer issue of the Journal Economic Perspectives and in Piketty (2014).

[2]See also the review by Benhabib & Bisin (2017). Saez & Zucman (2016) emphasize the role of differential savings rates, rather than differential rates of return, in generating wealth inequality. However, their capitalization method imposes homogeneity across investors on the rates of return within asset classes, thereby ruling out one mechanism over the other.

cess information about asset payoffs, and by their choice of how to allocate this capacity across assets.[3] We model the learning choice using the theory of rational inattention of Sims (2003). While stylized, the framework captures several appealing aspects of learning. First, getting information about one's investments requires expending resources. Second, learning about more volatile assets consumes more resources. Lastly, investors can allocate their information capacity optimally across different types of assets, depending on their objective and the characteristics of the assets they invest in. Our theoretical framework generalizes existing models—Van Nieuwerburgh & Veldkamp (2010) in particular—by considering heterogeneously informed agents investing in multiple heterogeneous assets.[4]

We analytically characterize three channels of how investor heterogeneity generates capital income inequality: Investors with higher information capacity hold larger portfolios on average, tilt their average holdings towards riskier assets within the risky portfolio, and adjust their investments more aggressively in response to changes in payoffs. These patterns are consistent with the empirical literature on portfolio composition differences between wealthy and less wealthy investors, going back to Greenwood (1983), and Mankiw & Zeldes (1991), and discussed more recently by Fagereng et al. (2016b) and Bach, Calvet & Sodini (2015).

Our central result is that growth in aggregate information capacity, interpreted as a general progress in information-processing technologies, disproportionately benefits the initially more skilled investors, and leads to growing capital income inequality. As the aggregate

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[3]In the model, we endow each investor with a particular level of information processing capacity. However, this capacity should be interpreted more broadly, as a stand-in for the individual's ability to access high quality investment advice, not limited to his or her own knowledge of or ability to invest in financial markets.

[4]In finance, rational inattention models have been used successfully to address underdiversification puzzles, price volatility and comovement puzzles, overconfidence, and the home bias, among other applications. References include Peng (2005), Peng & Xiong (2006), Van Nieuwerburgh & Veldkamp (2009; 2010), Mondria (2010). See also Maćkowiak & Wiederholt (2009; 2015), Matějka (2015), and Stevens (2018) for applications in macroeconomics. Our application to inequality is new, to our knowledge.

capacity to process information grows, all investors would like to grow their portfolios. However, in equilibrium, prices increase in response to the higher demand, and only the sophisticated investors expand their portfolios. The less sophisticated investors are priced out and retrench to lower-risk, lower-return assets, which amplifies capital income inequality. This result holds regardless of the learning technology assumed, and the specific functional form for information acquisition only affects the magnitude of the effect.

Our mechanism is amplified in a setting with heterogeneous assets, because the shifts in ownership shares occur asymmetrically across assets. Allowing investors to choose how to learn about different assets is critical here: With endogenous information choice, the sophisticated ownership share grows most for the most volatile assets, which are precisely the assets that generate the largest capital income gains. As a result, the model with multiple risky assets generates more inequality growth compared with a model with one risky asset.

To provide some guidance regarding the magnitudes of the effects identified in our model, we conduct a set of numerical experiments in a parameterized economy. We show that a 5% annual growth in aggregate information capacity[5] generates a rise in capital income inequality of 38% over 24 years. In contrast, an economy with a single risky asset generates only 20% growth. Calibrating the information capacity growth is challenging because the information that investors have when they make their investment decisions is not observable. However, for a range of plausible values of recent growth in information capacity, inequality growth ranges from 24% to 60%. The corresponding number in the *Survey of Consumer Finances* (SCF) for the 1989-2013 period is 87%.[6] General progress in information technology also generates

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[5]This annual growth rate is chosen to generate an average market return of 7% in the model. We discuss the parameterization in detail in Section 4.

[6]We define capital income inequality as the ratio between the average capital income of the top 10% of investors by wealth and that of the bottom 90% of investors by wealth, conditioning on participation in

lower market returns, higher market turnover, and larger and more volatile portfolios. These predictions are broadly consistent with the data on turnover and ownership from CRSP and Morningstar on stocks and mutual funds over the last 25 years.

Our findings connect to the idea that generating the inequality in outcomes observed in the data requires linking rates of return to wealth–which is our indicator for access to better information on investment strategies.[7] This idea has a long history, going back to Aiyagari (1994), who discusses the wide disparities in portfolio compositions across the wealth distribution, emphasizing the fact that rich households are much more likely to hold risky assets. Subsequently, Krusell & Smith (1998) suggest that the data requires that wealthy agents have higher propensities to save, generate higher returns on savings, or both. Benhabib et al. (2011) and Gabaix, Lasry, Lions & Moll (2016) are recent theoretical treatments and Favilukis (2013), Cao & Luo (2017), and Kasa & Lei (2018) are related quantitative contributions. We complement this literature along two key dimensions. First, we study the within-period portfolio problem with multiple risky assets, rather than the dynamic savings decision with a single risky asset. Second, we study inequality in a general equilibrium context with endogenous returns, rather than with exogenous idiosyncratic investment returns. Both asset heterogeneity and the endogenous response of asset prices–and hence returns–are key sources of amplification for inequality.

Our work contributes to a broader literature on inequality in capital income, including the work on bequests (Cagetti & De Nardi (2006)), limited stock market participation (Guvenen, 2007; 2009), financial literacy (Lusardi, Michaud & Mitchell (2017)), and entrepreneurial tal-

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financial markets. The Appendix presents all variable definitions.

[7]This connection is motivated by evidence that has linked trading strategy sophistication to asset prices, wealth and income levels, such as Calvet, Campbell & Sodini (2009), Chien, Cole & Lustig (2011), and Vissing-Jorgensen (2004).

ent (Quadrini (1999)). Our focus on differences in access to information builds on the insights of Arrow (1987). The emphasis on skill rather than risk aversion differences is supported by the portfolio-level evidence of Fagereng et al. (2016a). See Pástor & Veronesi (2016) for a one-asset model with heterogeneity in risk aversion and exogenous entrepreneurial skill differences. Also related is Peress (2004) who examines the role of wealth and decreasing absolute risk aversion in information acquisition and investment in a one-asset model.

Section 2 presents the theory. Section 3 derives analytic predictions, which is quantified in Section 4. Section 5 presents additional corroborating evidence, and Section 6 concludes.

2   Theoretical Framework

We set up a portfolio choice model with investors constrained in their capacity to process information about asset payoffs. Both asset characteristics and investors are heterogeneous.

Setup   A continuum of investors of mass one, indexed by j, solve a sequence of portfolio choice problems, to maximize mean-variance utility over wealth W_j in each period, given risk aversion coefficient $\rho > 0$. The financial market consists of one risk-free asset, with price normalized to 1 and payoff r, and $n > 1$ risky assets, indexed by i, with prices p_i, and independent payoffs $z_i = \overline{z} + \varepsilon_i$, with $\varepsilon_i \sim \mathcal{N}\left(0, \sigma_i^2\right)$.[8] The risk-free asset has unlimited supply, and each risky asset has fixed supply, $\overline{x}$. For each risky asset, non-optimizing "noise traders" trade for reasons orthogonal to prices and payoffs (e.g., liquidity, hedging, or life-cycle reasons), such that the net supply available to the (optimizing) investors is $x_i = \overline{x} + \nu_i$,

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[8]Under certain simplifying assumptions about the investors' learning technology (namely the independence of signals across assets), assuming independent payoffs is without loss of generality. See Van Nieuwerburgh & Veldkamp (2010) for a discussion of how to orthogonalize correlated assets under such assumptions.

with $\nu_i \sim \mathcal{N}(0, \sigma_x^2)$, independent of payoffs and across assets.[9] Following Admati (1985), we conjecture that prices are $p_i = a_i + b_i \varepsilon_i - c_i \nu_i$, for some coefficients $a_i, b_i, c_i \geq 0$.

Investors know the distributions of the shocks, but not the realizations (ε_i, ν_i). Prior to making their portfolio decisions, investors can obtain information about some or all of the risky asset payoffs, in the form of signals. The informativeness of these signals is constrained by each investor's capacity to process information. We consider two investor types: mass $\lambda \in (0, 1)$ of investors, labeled *sophisticated*, have high capacity to process information, K_1, and mass $1 - \lambda$, labeled *unsophisticated*, have low capacity, K_2, with $0 < K_2 < K_1 < \infty$.

Higher capacity can be interpreted as having more resources to gather and process news about different assets, and it translates into signals that track the realized payoffs with higher precision. A bound on this capacity limits investors' ability to reduce uncertainty about payoffs. Given this constraint, they choose how to allocate attention across different assets. We use the reduction in the entropy (Shannon (1948)) of the payoffs conditional on the signals as a measure of how much capacity the chosen signals consume. Starting with Sims (2003), entropy reduction has become a frequently used measure of information in a variety of contexts in economics and finance. Entropy has a number of appealing properties as a measure of uncertainty. For example, for normally distributed random variables, it is linear in variance. Moreover, the entropy of a vector independent random variables is the sum of the entropies of the individual variables. While stylized, this learning process captures the key trade-offs investors face when deciding how to allocate their limited capacity across multiple investment decisions, as a function of their objective and of the risks they face.

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[9]For simplicity, we introduce heterogeneity only in the volatility of payoffs, although the model can easily accommodate additional heterogeneity in supply and in mean payoffs.

Individual optimization Optimization occurs in two stages. In the first stage, investors solve their information acquisition problem, and in the second stage, they choose portfolio holdings. We first solve the optimal portfolio choice in the second stage, for a given signal choice. We then solve for the ex-ante optimal signal choice.

Given prices and posterior beliefs, the investor chooses portfolio holdings to solve

$$U_j = \max_{\{q_{ji}\}_{i=1}^n} E_j(W_j) - \frac{\rho}{2} V_j(W_j) \tag{1}$$

$$s.t. \ \ W_j = r\left(W_{0j} - \sum_{i=1}^n q_{ji} p_i\right) + \sum_{i=1}^n q_{ji} z_i, \tag{2}$$

where E_j and V_j denote the mean and variance conditional on investor j's information set, and W_{0j} is initial wealth. Optimal portfolio holdings depend on the mean $\widehat{\mu}_{ji}$ and variance $\widehat{\sigma}_{ji}^2$ of investor j's posterior beliefs about the payoff z_i, and is given by $q_{ji} = \frac{\widehat{\mu}_{ji} - r p_i}{\rho \widehat{\sigma}_{ji}^2}$.

Given the optimal portfolio holdings as a function of beliefs, the ex-ante optimal distribution of signals maximizes ex-ante expected utility, $E_{0j}[U_j] = \frac{1}{2\rho} E_{0j}\left[\sum_{i=1}^n \frac{(\widehat{\mu}_{ji} - r p_i)^2}{\widehat{\sigma}_{ji}^2}\right]$. The choice of the vector of signals $s_j = (s_{j1}, ... s_{jn})$ about the vector of payoffs $z = (z_1, ..., z_n)$ is subject to the constraint $I(z; s_j) \leq K_j$, where K_j is the investor's capacity for processing news about the assets and $I(z; s_j)$ quantifies the reduction in the entropy of the payoffs, conditional on the vector of signals (defined below).

For analytical tractability, we assume that the signals s_{ji} are independent across assets and investors. Then, the total quantity of information obtained by an investor is the sum of the quantities of information obtained for each asset, $I(z_i; s_{ji})$. We can think of the information problem as a decomposition of each payoff into the signal component and a residual component that represents the information lost because of the investor's capacity constraint, $z_i = s_{ji} + \delta_{ji}$. If the signal and the residual are independent, then posterior beliefs

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are also normally distributed random variables, with mean $\widehat{\mu}_{ji} = s_{ji}$ and variance $\widehat{\sigma}_{ji}^2 = \sigma_{\delta ji}^2$. The investor chooses the precision of posterior beliefs for each asset to solve[10]

$$\max_{\{\widehat{\sigma}_{ji}^2\}_{i=1}^n} \sum_{i=1}^n G_i \frac{\sigma_i^2}{\widehat{\sigma}_{ji}^2} \quad s.t. \quad \frac{1}{2}\sum_{i=1}^n \log\left(\frac{\sigma_i^2}{\widehat{\sigma}_{ji}^2}\right) \le K_j, \tag{3}$$

$$G_i \equiv (1 - rb_i)^2 + \frac{r^2 c_i^2 \sigma_x^2}{\sigma_i^2} + \frac{(\overline{z} - ra_i)^2}{\sigma_i^2}, \tag{4}$$

where G_i are the utility gains from learning about asset i. These gains are a function of equilibrium prices and asset characteristics only; they are common across investor types, and taken as given by each investor.

Lemma 1. *The solution to the capacity allocation problem (3)-(4) is a corner: Each investor allocates capacity to reducing posterior uncertainty for the asset with the largest learning gain G_i. If multiple assets have equal gains, the investor randomizes among them.*

The linear objective and the convex constraint imply that each investor specializes, monitoring only one asset, regardless of her level of sophistication. For all other assets, portfolio holdings are determined by prior beliefs. If there are multiple assets are tied for the highest gain, the investor randomizes among them, with probabilities that are determined in equilibrium. But she continues to allocate all capacity to a single asset. Spreading individual capacity across multiple assets–even if they have equal gains from learning–would lower utility. This result extends the specialization results of Van Nieuwerburgh & Veldkamp (2010) to the case of heterogeneous assets and investors.

Equilibrium   Given the solution to the individual optimization problem, equilibrium prices are linear combinations of the shocks.

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[10]The investor's objective omits terms from the expected utility function that do not affect the optimization. See the Appendix for detailed derivations.

Lemma 2. *The price of asset i is given by $p_i = a_i + b_i \varepsilon_i - c_i \nu_i$, with*

$$a_i = \frac{1}{r} \left[\overline{z} - \frac{\rho \sigma_i^2 \overline{x}}{(1 + \Phi_i)} \right], \quad b_i = \frac{\Phi_i}{r (1 + \Phi_i)}, \quad c_i = \frac{\rho \sigma_i^2}{r (1 + \Phi_i)}, \tag{5}$$

$$\Phi_i \equiv m_{1i} \lambda \left(e^{2K_1} - 1 \right) + m_{2i}(1 - \lambda) \left(e^{2K_2} - 1 \right), \tag{6}$$

where Φ_i measures the information capacity allocated to learning about asset i in equilibrium, and $m_{1i}, m_{2i} \in [0, 1]$ are the fractions of sophisticated and unsophisticated investors who choose to learn about asset i.

Prices reflect payoff and supply shocks, with relative importance determined by amount of attention allocated to each asset, Φ_i. If there is no learning, the price only reflects the supply shock ν_i. As the attention allocated to an asset increases, the price co-moves more with the payoff. As $K_j \to \infty$, the price approaches the discounted realized payoff, z_i / r.

Given prices, we can now determine the allocation of attention across assets. Let assets be indexed so that $\sigma_i > \sigma_{i+1}$, and let $\xi_i \equiv \sigma_i^2 (\sigma_x^2 + \overline{x}^2)$ summarize the properties of asset i.

Lemma 3. *Let k denote the endogenous number of assets that are learned about. The allocation of information capacity across assets, $\{\Phi_i\}_{i=1}^n$, is uniquely pinned down by the conditions $G_i = \max_{h \in \{1,...,n\}} G_h$ for all $i \in \{1, ..., k\}$, and $G_i < \max_{h \in \{1,...,n\}} G_h$ for all $i \in \{k + 1, ..., n\}$, where in equilibrium the gain from learning about each asset is $G_i = \frac{1 + \rho^2 \xi_i}{(1 + \Phi_i)^2}$.*

The equilibrium gains from learning are asset-specific and depend only on the properties of the asset, ξ_i, and on the amount of attention devoted to that asset, across all investors, Φ_i. The model uniquely pins down the number of assets that are learned about and the amount of attention allocated to each asset. Aggregate capacity in the economy may be high enough that in equilibrium it is spread across multiple assets. In this case, each investor continues

to allocate her entire capacity to a single asset, but is now indifferent in terms of which of these assets to learn about. The investor randomizes, with the probability of learning about each asset being determined by the equilibrium conditions in Lemma 3.

With heterogeneous investor capacity, the model does not pin down how much attention each investor class contributes: All that matters is the total capacity Φ_i allocated to each asset. In the absence of empirical evidence to guide us on how the two groups are distributed, for our analytical and numerical results we will consider a symmetric distribution in which investors of the two types contribute capacity in proportion to their size in the population, so that $m_{1i} = m_{2i}$. This assumption is motivated by our result that the gains from learning are the same for the two investor types, so that it is not obvious why they would choose different strategies. It also implies that capacity can be written as $\Phi_i = \phi_i m_i$, with ϕ_i an exogenous measure of the economy's information capacity, which we will vary to explore how the model responds to technological progress in information.[11]

3 Predictions

In this section, we present analytic results implied by our information friction. Heterogeneous information implies differences in portfolio sizes, a different composition of the risky portfolio across investors, and different responsiveness to payoff shocks. Moreover, technological progress amplifies these forces, resulting in further growth in inequality.

The Effects of Heterogeneity on Inequality How do differences in capacity translate into differences in portfolio holdings and capital income? Let q_{1i} and q_{2i} denote the average

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[11]In Section 4, we investigate the sensitivity of our central results to this assumption.

per-capita holdings of asset i for sophisticated and unsophisticated investors, given by

$$q_{1i} = \left(\frac{\overline{z}_i - rp_i}{\rho \sigma_i^2} \right) + m_{1i} \left(e^{2K_1} - 1 \right) \left(\frac{z_i - rp_i}{\rho \sigma_i^2} \right), \tag{7}$$

and q_{2i} defined analogously. Equation (7) shows that per-capita holdings are the quantity that would be held under the investors' prior beliefs plus a quantity that is increasing in the realized excess return. The weight on the realized excess return is asset and investor specific. It is given by the amount of information capacity allocated to this asset by this investor group. Investors hold all assets, but invest relatively more in the asset they learn about. Hence, the model generates under-diversification of portfolios, consistent with the empirical evidence (e.g., Vissing-Jorgensen (2004) and references therein).

For actively traded assets, heterogeneity in capacities generates differences in ownership across investor types at the asset level. In a symmetric equilibrium, the average per-capita ownership difference, as a share of the supply of each asset, is

$$\frac{E\left[q_{1i} - q_{2i} \right]}{\overline{x}} = \left(e^{2K_1} - e^{2K_2} \right) \frac{m_i}{1 + \phi m_i} > 0. \tag{8}$$

Hence, the portfolio of the sophisticated investor is not simply a scaled up version of the unsophisticated portfolio. Rather, the portfolio weights *within* the class of risky assets also differ across the two investor types.

Proposition 1 (Ownership). *Let $k > 1$ be the number of assets actively traded in equilibrium. Then, for $i \in \{1, ..., k\}$,*

(i) $E\left[q_{1i} - q_{2i} \right] / \overline{x}$ is increasing in σ_i^2 and in $E\left[z_i - rp_i \right]$;

(ii) $q_{1i} - q_{2i}$ is increasing in realized excess returns $z_i - rp_i$.

Sophisticated investors hold a larger portfolio of risky assets on average, tilt their portfolio

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towards more volatile assets with higher expected excess returns, and adjust ownership, state by state, towards assets with higher *realized* excess returns.

To see the effects of the portfolio scale and composition differences on capital income, let capital income be $\pi_{ji} \equiv q_{ji} (z_i - rp_i)$. Average capital income diverges with the gap in capacities, differentially across assets i:

$$E [\pi_{1i} - \pi_{2i}] = \frac{1}{\rho} m_i G_i \left(e^{2K_1} - e^{2K_2} \right) > 0. \tag{9}$$

Proposition 2 (Capital Income). *Let $k > 1$ be the number of assets actively traded in equilibrium. Then, for $i \in \{1, ..., k\}$,*

(i) $E [\pi_{1i} - \pi_{2i}]$ is increasing in asset volatility σ_i;

(ii) $\pi_{1i} - \pi_{2i} \geq 0$, and is increasing in realized excess returns $z_i - rp_i$.

The average sophisticated investor realizes larger profits in states with positive excess returns, and incurs smaller losses in states with negative excess returns. The biggest difference in profits comes from investment in the more volatile, higher expected excess return assets. It is these volatile assets that drive inequality because they generate the biggest gain from learning, and hence the biggest advantage from having relatively high capacity.

To see the effects of an increase in capacity dispersion, consider an experiment in which dispersion rises but without changing the aggregate capacity in the economy.

Proposition 3 (Capacity Dispersion). *Let $k > 1$ be the number of assets actively traded in equilibrium. Consider an increase in capacity dispersion, $K_1' = K_1 + \Delta_1 > K_1$, $K_2' = K_2 - \Delta_2 < K_2$, with Δ_1 and Δ_2 such that the total information capacity ϕ remains unchanged. Then, for $i \in \{1, ..., k\}$,*

(i) Asset prices and excess returns remain unchanged.

(*ii*) *The difference in ownership shares* $(q_{1i} - q_{2i})/\overline{x}$ *increases.*

(*iii*) *Capital income gets more polarized as* π_{1i}/π_{2i} *increases state by state.*

Increasing dispersion in capacities while keeping aggregate capacity unchanged implies further polarization in holdings and capital income. As dispersion reaches its maximum level, unsophisticated investors approach zero capacity and invest based on their prior beliefs. However, dispersion in capacity has no effect on asset prices. Both the number of assets learned about and the mass of investors learning about each asset remain unchanged. Hence, the adjustment reflects a pure transfer of income from the relatively unsophisticated investors to the more sophisticated investors without any general equilibrium effects.

The Consequences of Growth in Capacity Our central result considers the effects of growth in aggregate capacity, interpreted as general progress in information-processing technologies. The effect of capacity growth on asset prices and inequality operate through its effects on the gains from learning and on the mass of investors learning about different assets. Figure 1 shows the evolution of masses and gains from learning as aggregate capacity grows. At low capacity, all investors learn about the most volatile asset, but as capacity grows, the gains from learning about this asset decline, and strategic substitutability in learning pushes some investors to learn about less volatile assets. The threshold that endogenizes single-asset learning as an optimal outcome is given by $\phi_1 \equiv \sqrt{\frac{1+\rho^2\xi_1}{1+\rho^2\xi_2}} - 1$. For capacity above ϕ_1, at least two assets are learned about and for sufficiently high information capacity, all assets are learned about.[12] Nevertheless, not all assets are learned about with the same intensity: The mass of investors who learn about an asset is decreasing in its volatility. This allocation

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[12]thus endogenizing the assumption employed in models with exogenous signals.

of attention affects the holdings across assets, and hence the investors' portfolio returns.

Proposition 4 (Symmetric Growth). *Let $k \leq 1$ be the number of assets actively traded in equilibrium. Consider an increase in aggregate capacity ϕ generated by a symmetric growth in capacities to $K_1' = (1 + \gamma) K_1$ and $K_2' = (1 + \gamma) K_2$, $\gamma \in (0, 1)$. Let $k' \geq k$ denote the new number of actively traded assets. For $i \in \{1, ..., k'\}$,*

(i) Average asset prices increase and average excess returns decrease, approaching the risk free rate in the limit.

(ii) Average ownership share of sophisticated investors $E[q_{1i}]/\overline{x}$ increases and average ownership share of unsophisticated investors $E[q_{2i}]/\overline{x}$ decreases, and the gap is increasing in asset volatility.

(iii) As long as the return on the risky portfolio exceeds the risk-free rate, average capital income gets more unequal, as $E[\pi_{1i}]/E[\pi_{2i}]$ increases, with inequality being higher for the more volatile assets.

Higher capacity to process information means that investors have more precise news about the realized payoffs, resulting in lower gains from learning, lower average returns, and larger and more volatile positions. However, as asset prices increase and returns decline, inequality keeps increasing. Sophisticated investors increase their ownership share at the expense of the less sophisticated investors, who retreat. This pecuniary externality arises regardless of the learning technology, since it is due to the fact that posterior variance is lower for the sophisticated investors, and hence on average they want to hold a larger quantity than the unsophisticated investors. Moreover, the increase in ownership is larger for the more volatile assets that have higher gains from learning and generate higher expected

returns. Hence, asset heterogeneity combined with endogenous information choice generates differential ownership growth that in turn amplifies the growth in inequality.

As capacity continues to grow, the decline in returns eventually becomes a mitigating factor in the growth of income inequality. Intuitively, if market returns are close to the risk free rate, then there is less scope in the economy for extracting informational rents. Capital income inequality peaks as rates of return reach the risk free rate. It subsequently starts to decline, and eventually, it stabilizes at a level implied by the differences in risk-free return income earned on on previously accumulated wealth. In the limit, all information is revealed and capital income inequality becomes flat. This process is shown in Figure 2.

4   Quantitative Analysis

So far, we have found that progress in information technology can qualitatively generate growing capital income inequality, through changes in both portfolio size and composition across investors. We now parameterize the model to provide some guidance for the magnitudes implied by this mechanism. We use data on household capital income from the SCF and data on the financial market from CRSP. We parameterize the model based on data from the first half of the SCF sample (1989-2000), and then we consider an experiment in which aggregate information capacity in the economy grows at a constant rate, to generate predictions for the second half of the sample (2001-2013).

4.1 Technological Progress and Inequality Growth

Table 1 presents parameter values and targets for the baseline results. The parameters characterizing the financial market are the risk free rate, $r = 2.5\%$, which matches the 3-month T-bill rate net of inflation over the period, the number of risky assets, n, which we set to 10 arbitrarily, and the means and volatilities of payoffs and noise shocks. In the absence of detailed information regarding holdings of different types of securities at the household level, we target volatility moments from the U.S. equities market. We set the dispersion in the volatilities of asset payoffs σ_i to target a dispersion in idiosyncratic return volatilities of 3.54, as measured by the the ratio of the 90th percentile to the median of the cross-sectional idiosyncratic volatility of stock returns.[13] We set the volatility of shocks from noise traders to $\sigma_x = 0.4$ to target an average monthly turnover (defined as the total monthly volume divided by the number of shares outstanding), equal to 9.7%. We normalize the level of prices by normalizing the mean payoff and the mean supply for each asset to $\bar{z}_i = 10$, $\bar{x}_i = 5$.[14]

The investor-level parameters we need to pin down are the risk aversion coefficient ρ, the information capacities of the two investor types (K_1, K_2), and the fraction of sophisticated investors (λ). We select those parameters to target the market return of 11.9% (corresponding to 1989-2000 average); the fraction of assets that investors learn about, which, in the absence of empirical guidance, we set to 50%; the equity ownership share of sophisticated investors of 69%; and the return spread between sophisticated and unsophisticated households of four percentage points. To compute the last two moments, we use data from the

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[13]We normalize the lowest volatility to $\sigma_n = 1$, and we set $\sigma_i = \sigma_n + \alpha(n - i)/n$, which implies the volatility distribution is linear. The dispersion target generates a slope coefficient $\alpha = 0.65$.

[14]Changing the number of assets in the parameterization does not have a major impact on our results.

Survey of Consumer Finances. Although not as comprehensive as tax records data, the SCF provides detailed information about the balance sheets of a representative sample of U.S. households.[15] We restrict our sample to participants in financial markets, defined as households that report holding stocks, bonds, mutual funds, receiving dividends, or having a brokerage account. On average, 34% of households participate.[16] We classify as sophisticated investors the participants in the top decile of the wealth distribution, and relatively unsophisticated investors as the remaining 90% of participants.[17] Using this definition, the equity ownership share of sophisticated investors is 69%.[18]

In order to quantify the return heterogeneity, for each household, we compute capital income divided by holdings of risky securities (stocks, bonds, and mutual funds), and then use these return measures to capture the heterogeneity between the two groups of households. Specifically, we compute the ratio of the median return of the unsophisticated households relative to the median return of the sophisticated households, which is 69.2% over the first half of the sample. We use this gap to obtain targets for the levels of returns of each household type, given the market return. The weights used in computing the aggregate return are the fraction of risky securities held by each type of household in the SCF (31%

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[15]We use the weights provided in the public use data sets of the SCF in order to make the results representative of the population of U.S. households. These weights account for both the oversampling of wealthy households and for differential patterns of nonresponse. For a discussion of weights and aggregate analysis of the quality of SCF data, see Kennickell & Woodburn (1999) and Kennickell (2000). See also Saez & Zucman (2016) for a detailed comparison of the SCF to U.S. administrative tax data. In short, they find that the SCF is representative of trends and levels of inequality in the U.S., but understates inequality inside the top 1% of the wealth distribution.

[16]We also consider a broader measure of participation that includes all households with equity in a retirement account. This raises the participation rates, but does not alter our main findings.

[17]In the Appendix, we show that in the data people with higher initial wealth use more sophisticated investment instruments, hold larger portfolios, and invest a lower proportion of their assets in money-like instruments. Additional evidence that links wealth to investment sophistication includes Calvet et al. (2009) and Vissing-Jorgensen (2004).

[18]To compute the number, we first compute the dollar value of the risky part of the financial holdings of households (stocks, bonds, non-money market funds, and other financials) for each decile of the wealth distribution. Then, we compute the share of these risky assets held by the top decile.

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versus 69%). That gives us the difference between sophisticated and unsophisticated returns of four percentage points, which together with the target for market return above implies the target for sophisticated return of 13.1% and the unsophisticated return of 9.1%.[19]

Table 2 presents the model's response to aggregate capacity growth chosen to match the market return in the entire sample of 7%. It implies a 4.9% growth in capacity and additionally generates an increase in trading volume, as better informed investors adjust their holdings more aggressively. Quantitatively, a capacity growth of 4.9% over 24 years generates a decline in market returns to 2.6%, bringing the average return for the entire period to 7%, as in the data, while turnover increases from 9.7% in the first half of the sample to 16.8% in the second half, versus 16.0% in the data. This technological progress leads to higher capital income inequality, which grows by 38% over the period. This figure suggests that aggregate capacity growth is quite potent in generating capital income inequality growth. For reference, in the corresponding period capital income inequality growth in the SCF equals 87%.[20]

Inequality grows due to two main effects: (i) larger relative exposure of sophisticated investors to the asset market, marked by higher ownership shares across all assets, and (ii) a shift of sophisticated investors towards high risk, high return assets and that of unsophisticated investors towards lower risk and lower return assets. As capacity increases, less sophisticated investors are priced out of trading the more risky assets and shift their portfolio weights towards less risky, lower-return assets. As a result, the ownership share of sophisticated investors, relative to their population share, rises relatively more for the assets that

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[19]We perform a detailed grid search over parameters until all the simulated moments are within a 10% distance from target. That gives sophisticated ownership within 0.7%, sophisticated and unsophisticated returns within 7%, ratio of volatilities within 2% and all other targets matched exactly.

[20]We compute this inequality growth as follows. For each survey year, we sort the sample of participants by the level of total wealth, and we calculate inequality as the ratio of average capital income of the top 10% to that of the bottom 90% of participants.

are above the median in terms of volatility relative to the assets that are below the median in terms of volatility. For both types of assets, sophisticated owners are over-represented relative to their size in the population (both numbers are greater than 1), reflecting their larger overall portfolios. But the difference is larger for the more volatile assets: at the end of the simulation period, sophisticated investors hold 21% more of high-risk assets relative to their population weight, compared to 14% more for low-risk assets. This gap measures the retrenchment of unsophisticated investors from the most profitable assets.

To isolate the effects due to portfolio composition and volatility dispersion, we solve and parameterize our model with just one risky asset. In a one asset economy, the rates of return on risky portfolios–which we use in the calibration of the benchmark model–are the same across the two types of investors, since there is now only one risky asset. The differences in capital income come only from the differences in holdings of the risky asset, both on average and state by state. Hence, we use ownership and turnover to discipline the one-asset numerical exercise. The resulting growth in capital income inequality is almost half of the growth generated by the benchmark model: 20% versus 38%. Hence, the different exposure to assets with different characteristics, and the asymmetric shifting of weights across assets as capacity grows play a significant role in driving capital income inequality.[21]

Our growth simulation increases the relative share of the sophisticated group in the

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[21]In terms of the parameterization, the model with one risky asset takes away three targets from the benchmark model: heterogeneity in asset volatility, fraction of actively traded assets, and the return difference between sophisticated and unsophisticated investors. We keep the value of the risk aversion coefficient the same as in the benchmark model and set the volatility of the single asset payoff equal to the median payoff volatility of the benchmark model. That leaves three parameters: volatility of the noise trader demand σ_x, and the two capacities of sophisticated and unsophisticated investors. We choose these to match: the average market return, the average asset turnover, and the share of sophisticated ownership. That gives $(K_1, K_2, \sigma_x) = (0.0544, 0.0163, 0.37)$. In the dynamic simulation, we pick the growth rate of aggregate capacity to match the decline in the market return (just as in the benchmark simulation). That implies a 6.7% growth rate of technology.

economy's total information capacity ϕ. To quantify the relevance of this force, we consider a simulation in which we grow capacity differentially so as to keep the shares of relative capacity of the investor types constant at the levels in the initial period. This change results in an inequality growth of 32% versus the benchmark 38%. The relatively limited effect reflects the fact that the sophisticated share in overall capacity is high to begin with.[22]

Calibrating the information capacity growth is challenging because the information that investors have when they make their investment decisions is not observable. Hence, our strategy is to set capacity growth so as to match the decline in market returns seen in the data, and to complement these results with robustness checks on this growth rate. We consider two alternative annual growth rates: 4% and 8%, based on the annual growth rate of the number of stocks actively analyzed by the financial industry, and the growth rate of the number of analysts per stock in the financial industry, respectively.[23] These rates imply 24% and 60% inequality growth. Although the results are sensitive to the growth rate of information capacity, the model generates a quantitatively significant rise in capital income inequality relative to the data.

4.2 Robustness

Two features of our specification have important implications for our results: the information acquisition technology and the equilibrium selection mechanism. We now discuss how changing our assumptions along these two dimensions affects inequality.

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[22]In the Online Appendix, we also provide an exercise in which the capacity grows in proportion to the rates of return of the portfolio, capturing explicitly the idea that capacity is linked to wealth. That exacerbates the growth in inequality. Keeping the average capacity growth the same as in the benchmark economy, linking capacity growth to returns implies a 49% increase in capital income inequality.

[23]Our information friction implies that growth in information capacity translates into growth in actively analyzed stocks, and also more information capacity allocated per stock, consistent with these growth trends

Marginal Cost Predictions In our benchmark model, we endow each investor with some level of capacity to process information. What happens to investor choices and inequality if we model a marginal cost of acquiring information instead? Let investors differ in their marginal cost of information, $0 < \kappa_1 < \kappa_2$. Then the investor's objective becomes $\max_{\{v_{ji}\}_{i=1}^n} \sum_{i=1}^n \left[G_i \frac{\sigma_i^2}{\hat{\sigma}_{ji}^2} - \frac{\kappa_j}{2} \log \frac{\sigma_i^2}{\hat{\sigma}_{ji}^2} \right]$, and the information problem is independent across assets as investors decide how much information to purchase for each asset separately. Hence, instead of a corner solution for learning, each investor purchases information about all assets whose gains exceed their marginal cost, up to the point at which the gain from learning reaches the marginal cost. In equilibrium, the gains from learning decline endogenously the more information investors purchase and the sophisticated, low marginal cost investors are the marginal buyers of information, driving the gains from learning down to *their* marginal cost for all assets. The unsophisticated investors, who have a higher marginal cost, are now priced out of the information market altogether. As in the benchmark case, there is a preference for volatility, with the quantity of information purchased declining with asset volatility. The difference is that now for each asset, either the gains from learning are too small relative to the costs that *neither* investor learns about it, *or* only the sophisticated investors learn about it. For a given amount of information in the economy, the marginal cost specification results in larger inequality in both holdings and capital income relative to the endowed capacity case, in which both types of investors learn. Moreover, technological progress in information processing has no direct effect on the unsophisticated investors: As long as their marginal cost remains above that of the sophisticated investor, they purchase no information and invest in all assets according to their prior beliefs.

Asymmetric Equilibrium Predictions   In our benchmark model, we pin down the total amount of capacity devoted to each asset, but not the contribution of each investor group to that total. When deriving our analytic and numerical results, we impose a symmetric equilibrium, assuming that the fraction of investors that learn about each asset is the same for both investor types. We base this assumption on our result that the gains from learning about different assets are the same for both sophisticated and unsophisticated investors. However, the same equilibrium allocation of attention (and hence asset prices) could be achieved with a different distribution of investors across assets. How sensitive are our results to deviations from the symmetric equilibrium? First, it is useful to note that all our results hold at the individual level: If we compare two investors who both monitor the same asset, one sophisticated and one unsophisticated, they will differ in their holdings, capital income, and response to capacity growth as expected. But when we compare the average holdings of the two groups, asset-level predictions depend on how many investors learn about the asset in each group. It is possible to conceive of an allocation of investors across assets such that for some assets, the per capita ownership of unsophisticated investors is larger than that of the sophisticated investors. But it remains the case that on average across all assets the per capita ownership–and hence capital income–of the unsophisticated investors is strictly lower than that of the sophisticated investors. Moreover, growth in aggregate capacity continues to increase capital income inequality (as long as returns remain above the risk free rate), even if we consider a reshuffling of masses most advantageous to the unsophisticated investors, namely one that assigns all the unsophisticated investors learning about an asset to the highest volatility asset. Such a reshuffling yields positive, albeit lower, inequality growth. Numerically, we find that in our parameterized economy such a reshuffling has minimal

effects on inequality growth (reducing it by less than one percentage point), because the data favor a parameterization in which the unsophisticated investors contribute minimally to the allocation of attention for each asset, so that how we reshuffle them across assets has very limited effects on the dispersion of ownership and capital income.

5   Empirical Evidence

We now provide auxiliary evidence supporting our mechanism and its implications.

Skill versus Risk   How much of the growth in inequality comes from differences in exposure to risk versus differences in skill? Our model is one in which both risk-taking differences and pure compensation for skill generate return heterogeneity. Sophisticated investors are more exposed to risk because they choose to hold a larger share of risky assets (compensation for risk); and because they have an informational advantage (compensation for skill). Quantitatively, in our model the compensation for skill accounts for approximately 75% of the return differential between the two investor groups, with the remaining 25% reflecting more risk taking.[24]

Empirically, Fagereng et al. (2016a) document that risk taking is only partially responsible for the difference in returns among Norwegian households, with approximately half of the return difference being attributed to unobservable heterogeneity. Corroborating this finding, we consider more aggregated data from the U.S. financial market. We compare returns from different types of mutual funds, using data from Morningstar, which contains information for two types of funds: those with a minimum investment of $100,000 (institutional funds)

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[24]The Appendix presents the details of the calculation.

and those without such restrictions (retail funds). These two types of funds are suggestive of the kind of investment returns sophisticated versus unsophisticated investors can access. Since the institutional funds have a minimum investment threshold, less sophisticated, less wealthy investors do not have access to the higher returns earned by institutional funds, even for "plain vanilla" assets like equities.[25] Our fund data span the period 1989 through 2012. We compare the returns of the two groups adjusting for differences in exposure to common risk factors, a methodology that is standard in asset pricing literature. Our choice of common risk factors follows Carhart (1997) and includes market excess returns, return on the size factor, return on the value factor, and return on the momentum factor. To compute quantitative differences between the two investor groups we calculate a hedge portfolio, defined as a difference between monthly returns on the sophisticated portfolio and monthly returns on the unsophisticated portfolio. We then estimate the time-series regression of the hedge returns on the four factors. Our coefficient of interest is an intercept, which measures abnormal returns over and above premia for risk. The hedge portfolio generates a statistically significant positive return of 33 basis points per month, which is almost 4% on an annual basis. Hence, we conclude that differences in risk exposures alone are unlikely to explain the differences in returns between sophisticated and unsophisticated investors.

Nevertheless, by shutting down the risk aversion channel, we are likely minimizing the effect that risk has on inequality outcomes. The overall growth in inequality can be increased by assuming either decreasing absolute risk aversion or differences in risk attitudes that, like information capacity, are correlated with wealth. The less risk averse investors would hold

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[25]In the Appendix, we present additional evidence that the there are both institutional and informational barriers that prevent unsophisticated households from gaining access and delegating their investment decisions to high quality investment services.

a greater share of risky assets, and hence they would have higher expected capital income.[26] In a CRRA framework, the model solution under no capacity differences predicts the same portfolio shares for risky assets, *independent of wealth.* Intuitively, if agents have common information, then wealth differences affect the composition of their allocations between the risk-free asset and the risky portfolio, but not the composition of the risky portfolio, which is determined optimally by the (common) belief structure. As a result, differences in capacity are a necessary component for the model to generate any risky return differences across agents. Similarly, within our mean-variance specification, a growing difference in risk aversion produces growing *aggregate* ownership in risky assets of less risk averse investors, and a uniform, proportional retrenchment from all risky assets of more risk averse investors. However, heterogeneity in risk aversion alone cannot generate the empirical investor-specific rates of return on equity, differences in portfolio weights within a class of risky assets or differential growth in ownership by asset volatility. Hence, the information asymmetry remains central to matching several recent trends in U.S. financial markets.[27]

The Extensive Margin of Limited Participation   Limited participation in U.S. financial markets has long been a source of inequality in total income and wealth (e.g., Mankiw & Zeldes (1991)). How important is the limited participation margin for generating capital income inequality? Using data from the SCF, we find that much of the recent growth in financial wealth inequality has occurred among household who participate in financial markets, and that trends in capital income growth mirror trends in total financial wealth

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[26]Such setting would also encompass situations in which investors are exposed to different levels of volatility in areas outside capital markets, like labor income.

[27]Additionally, Gomez (2016) shows that when macro asset pricing models with heterogenous risk aversion are parameterized to match the volatility of asset prices, they require a degree of heterogeneity in preferences that leads to counterfactual predictions about wealth inequality.

inequality. Our evidence on capital income inequality reinforces existing results using more detailed U.S. and European data, e.g. Saez & Zucman (2016), Fagereng et al. (2016b) and Bach et al. (2015).

First, participation is hump-shaped over time. Moreover, inequality in total financial wealth has grown within the group of households who participate in financial markets, but it has remained essentially unchanged along the extensive margin (defined as the ratio of average financial wealth of the bottom 10% of participating households to that of the non-participating households). Thus the dynamics of financial wealth inequality do not appear to be driven by the participation margin. These trends are shown in Figure 3 and Figure 4.[28]

Second, among participants, the increase in inequality in financial wealth tracks the accumulation of capital income from the risky assets (namely, income from dividends, interest income, and realized capital gains). To see this, we consider the counterfactual financial wealth obtained from accruing capital income only.[29] Figure 5 suggests that past capital income realizations may be sufficient to explain the evolution of financial wealth inequality, without resorting to mechanisms that involve savings rates from other income sources.[30]

Third, among participating households, capital income inequality is large and growing fast. Panel (a) of Figure 7 shows that in the cross-section, capital income is an order of magnitude more unequal than either labor or total income. For example, in 1989, the average capital income of the top 10% of participants was 21 times larger than that of the

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[28]Financial wealth in the SCF contains holdings of risky assets (stocks, bonds, mutual funds), passive assets (life insurance, retirement accounts, royalties, annuities, trusts), and liquid assets (cash, checking and savings accounts, money market accounts).

[29]For example, the counterfactual financial wealth level in 1995 is equal to the actual financial wealth in 1989 plus 3 times the capital income reported in the prior survey years (in this case, 1989 and 1992).

[30]By construction, the two wealth levels are identical in 1989, so the figure also implies that the counterfactual levels of financial wealth for each group are very close to those in the data. Still, we treat this evidence as suggestive, since our exercise imposes a panel interpretation on a repeated cross-section.

bottom 90% of participants. This ratio increased to nearly 40 in 2013. By comparison, the corresponding ratio for wage income was 2.4 in 1989 and 3.9 in 2013. To compare the dynamics of inequality across income sources, we normalize the inequality of each income measure to 1 in 1989, and plot growth rates for capital, labor, and total income inequality in panel (b) of the figure. As is well known, labor income inequality has grown significantly during this period, and so has capital income inequality, which nearly doubled.

We complement this evidence with additional data on flows into and out of mutual funds from Morningstar by sophisticated (institutional) and unsophisticated (retail) investors. As shown in Figure 6, the cumulative flows from sophisticated investors into equity and non-equity funds increase steadily over the entire sample period. In contrast, since 2000, unsophisticated investors have been shifting their funds out of equity mutual funds and into less risky non-equity funds. To the extent that direct equity holdings are more risky than diversified equity portfolios, such as mutual funds, this implies that unsophisticated investors have been systematically reallocating their wealth from riskier to safer asset classes. This trend is consistent with our model, which predicts that as aggregate capacity grows, sophisticated investors expand their ownership of risky assets by order of volatility: starting from the highest volatility assets and then moving down.

6   Concluding Remarks

What contributes to the growing capital income inequality across households? We propose a theoretical information-based framework that links capital income to investor sophistication. Our model implies income inequality that rises with the total information in the

market. Predictions on asset ownership, market returns, and turnover provide additional support for the economic mechanism we propose.

The overall growth of investment resources and competition among investors with different skill levels are generally considered signs of a well-functioning financial market. Our work highlights how advances in information processing technologies also have consequences beyond the financial market, affecting the distribution of income.

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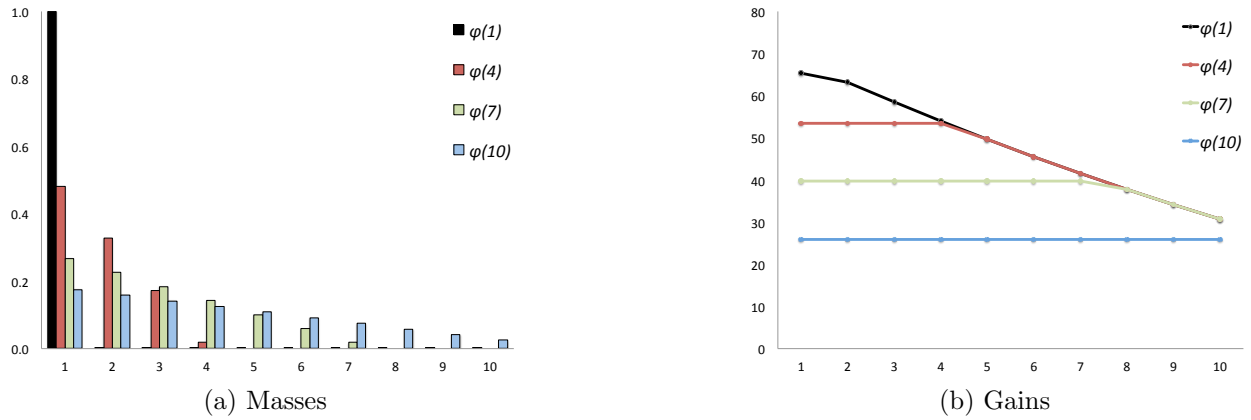
(a) Masses

(b) Gains

Figure 1: The evolution of masses and gains from learning as aggregate capacity is increased. $\phi(k)$ indicates the level of aggregate capacity for which k assets are learned about in equilibrium. Gains are higher for higher volatility assets. As capacity increases, gains fall. Gains are equated for all assets that are learned about in equilibrium. On the x-axis, assets are ordered from most (1) to least (10) volatile.
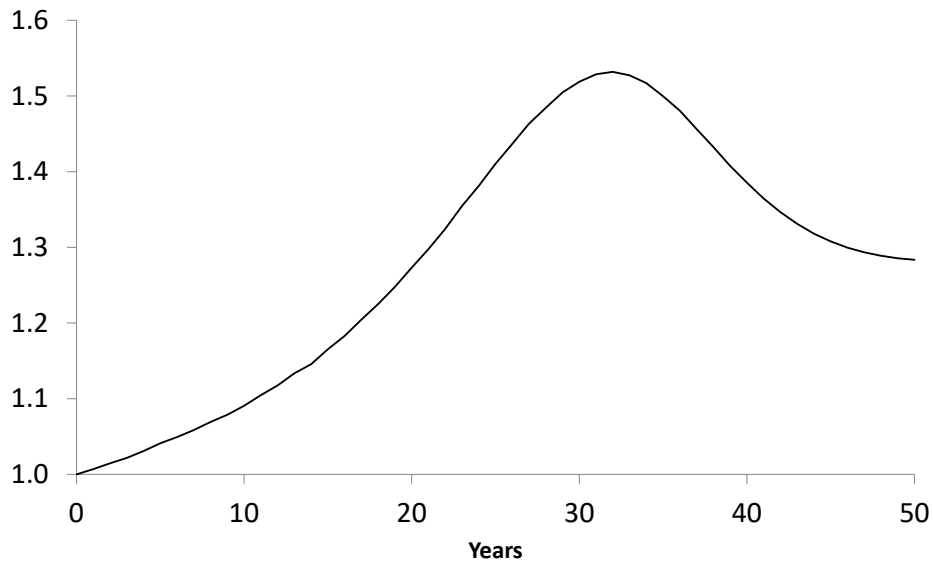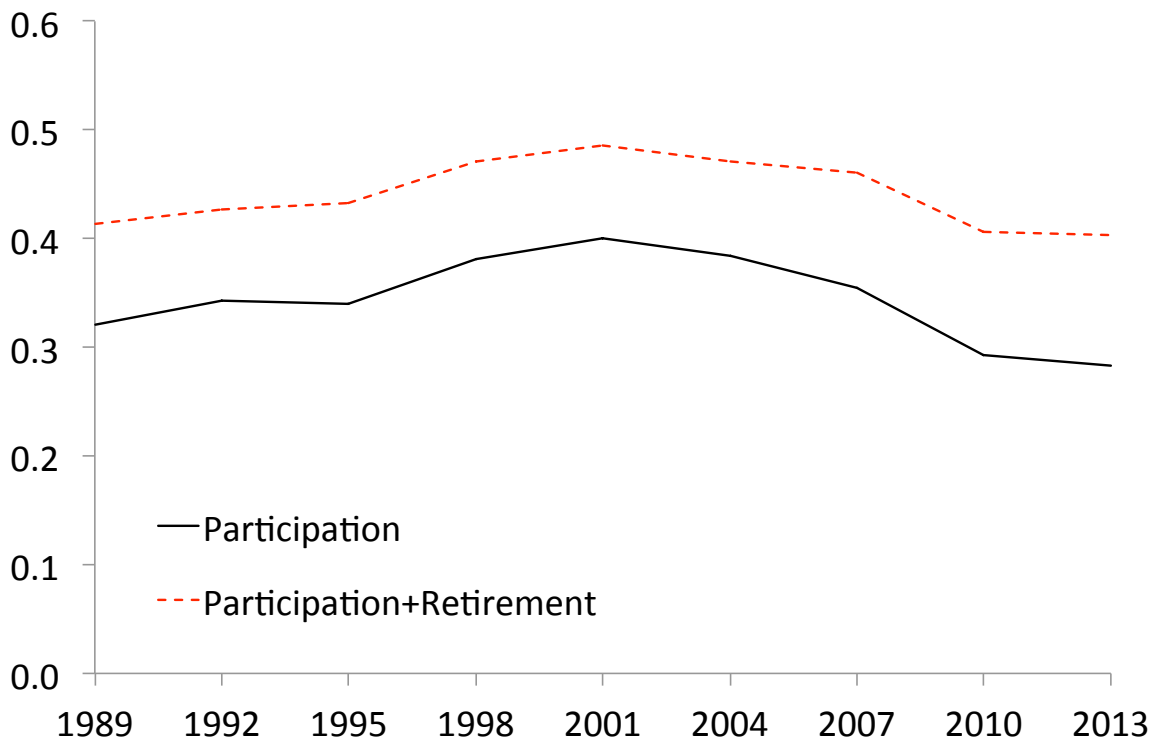

Figure 2: Model: capital income inequality in the long run.

Figure 3: Financial markets participation in the SCF. Participants are individuals who have a brokerage account or who report stock holdings, bonds, money market funds, or non-money market funds. For a broader measure, we also consider households who have equity in retirement accounts.
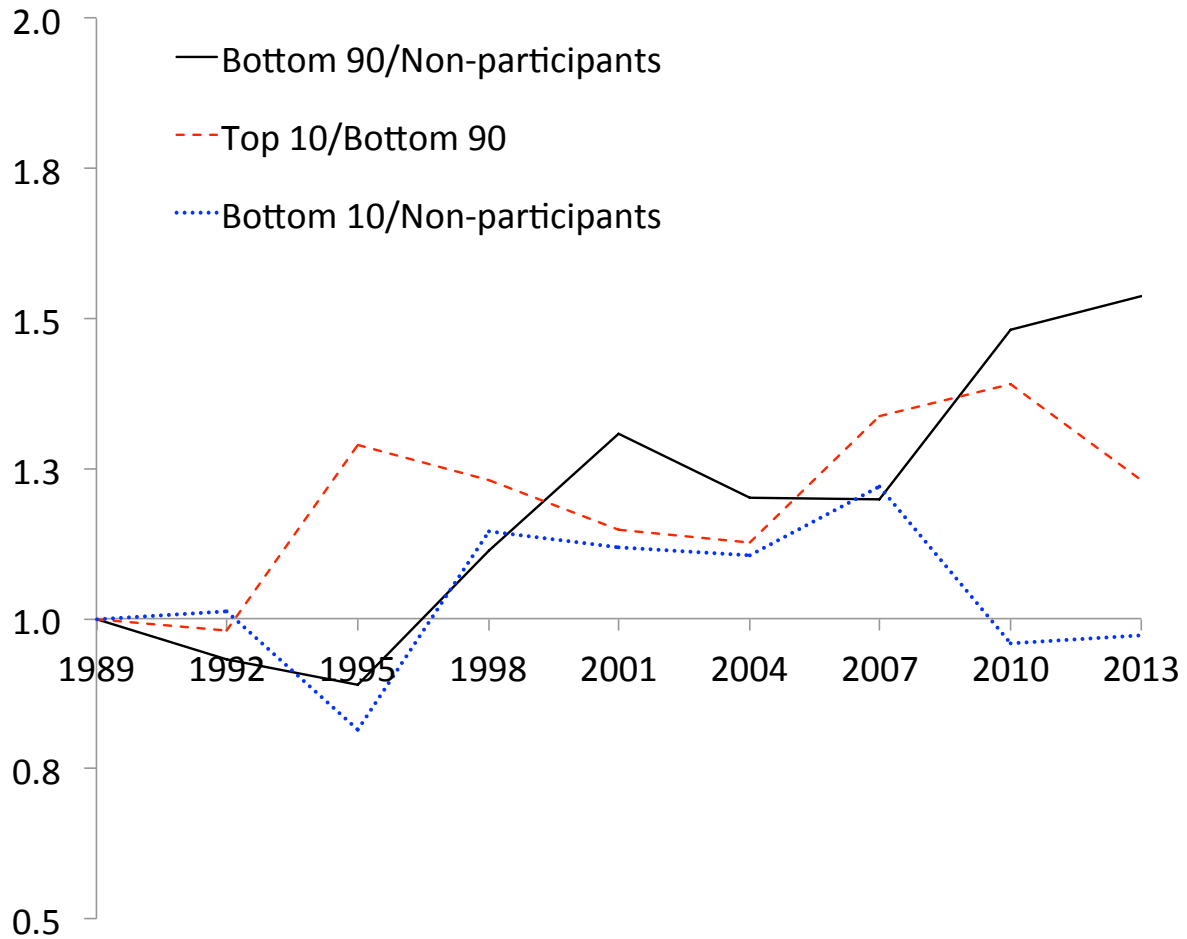
Figure 4: Extensive and intensive margins in financial wealth inequality in the SCF. 'Top 10/Bottom 90' measures inequality within the group of participants, defined as the ratio of financial wealth of the top wealth decile to that of the bottom 90% of participants. 'Bottom 10/Non-participants' measures inequality at the participation margin, measured as the ratio of financial wealth of the bottom 10% of participating households to that of all non-participating households.
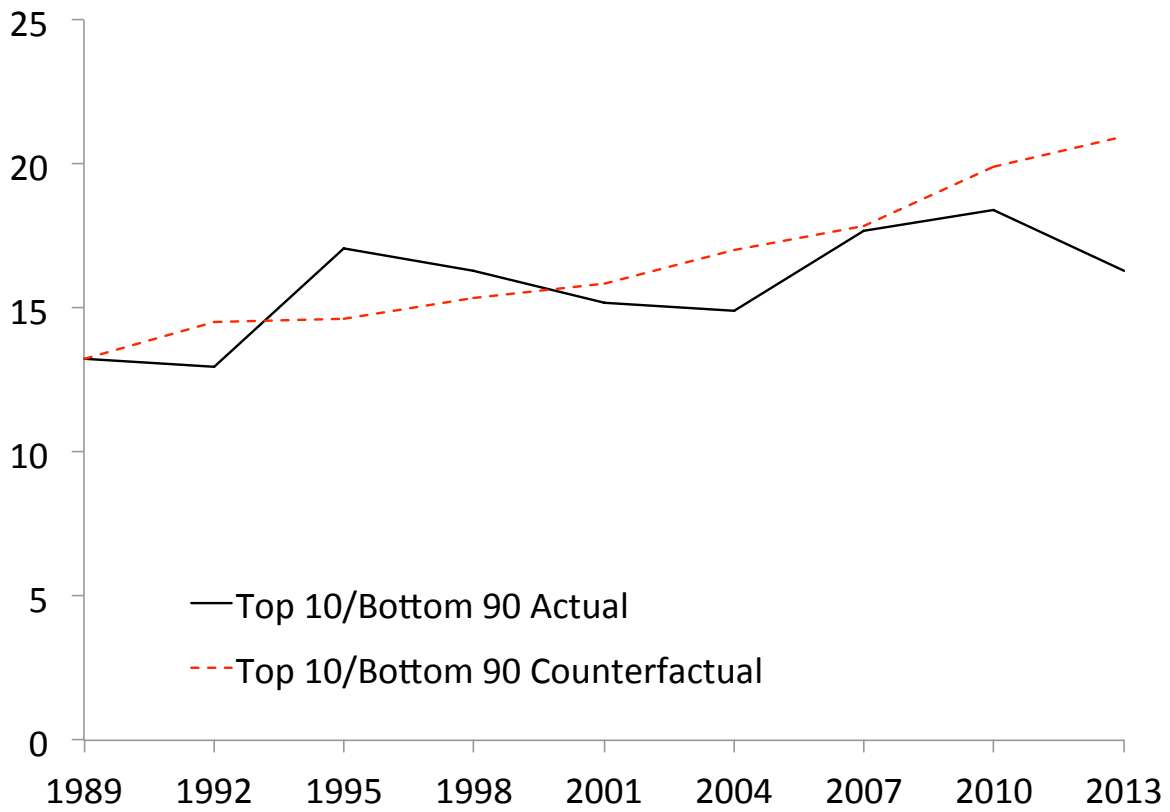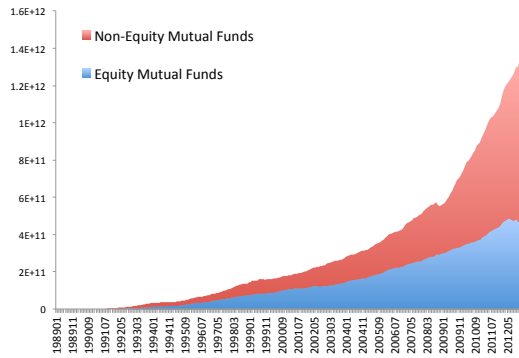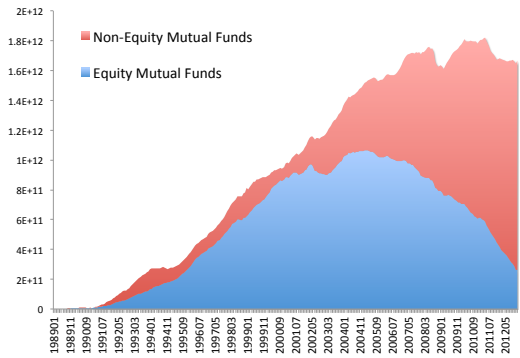
Figure 5: Financial wealth inequality and counterfactual financial wealth inequality constructed by accruing capital income.

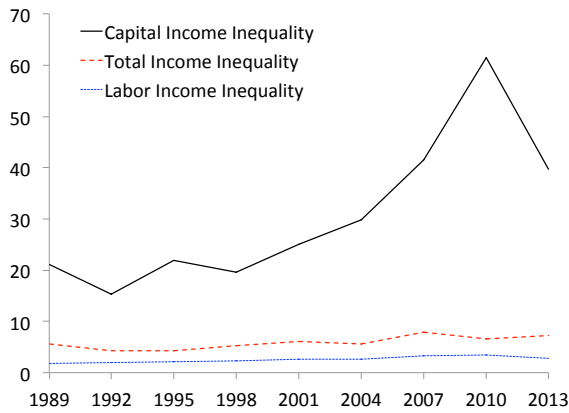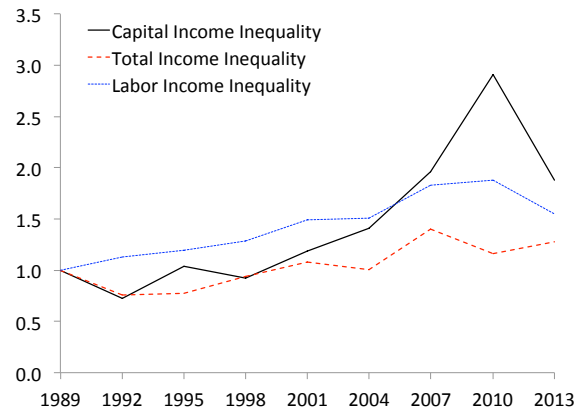Figure 6: Cumulative Flows to Mutual Funds: Institutional versus Retail Funds. Morningstar data.

Figure 7: Income inequality growth in the SCF. Inequality is the ratio of the top 10% to the bottom 90% (in terms of total wealth) of participants in financial markets. (a) Inequality for capital income, labor income and other income in levels. (b) Same series, normalized to 1 in 1989.

Table 1: Parameter Values in the Baseline Model

Parameter	Symbol	Value	Target (1989-2000 averages)
Risk-free rate	r	2.5%	3-month T-bill $-$ inflation $= 2.5\%$
Number of assets	n	10	Normalization
Vol. of asset payoffs	σ_i	$\in [1, 1.59]$	p90/p50 of idio. return vol $= 3.54$
Vol. of noise shocks	σ_{xi}	0.4 for all i	Average turnover $= 9.7\%$
Mean payoff, supply	$\bar{z}_i, \bar{x}_i$	10, 5 for all i	Normalization
Risk aversion	ρ	1.032	Average return $= 11.9\%$
Information capacities	K_1, K_2	0.37, 0.0037,	Sophisticated share $= 69\%$
and investor masses	λ	0.675	Share actively traded $= 50\%$
			Sophisticated return $= 13.1\%$

Note: Data are from CRSP for idiosyncratic stock return volatility, turnover, and average return and from SCF for return spread and sophisticated ownership share. Targets are for the 1989-2000 period.

Table 2: Aggregate Capacity Growth Outcomes

Statistic	Baseline	Data	
Capacity growth (%)	4.9		
Average market return (%)	7	7	
Capital income inequality growth (%)	38	87	
Sophis ending ownership share, top	1.21		
Sophis ending ownership share, bottom	1.14		
	One asset	Low growth	High growth
Capacity growth (%)	6.7	4	8
Average market return (%)	7	8	5
Capital income inequality growth (%)	20	24	60
Sophis ending ownership share, top	1.1	1.16	1.43
Sophis ending ownership share, bottom		1.08	1.41

Note: The average market return is the market return over the entire 1989-2013 period, and is targeted in the baseline and one-asset economy. All other numbers are not targeted. "Sophis ownership share" represents the ownership share of sophisticated investors, relative to their population share, for the assets that are above the median in terms of volatility ("top") and for assets that are below the median in terms of volatility ("bottom"), at the end of the simulation period. In the one-asset economy, it represents the sophisticated ownership share in the one risky asset.