Return Heterogeneity, Information Frictions, and Economic Shocks

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Abstract

This paper studies the effects of information frictions on returns to net worth and how these frictions amplify economic shock to the economy. Using a panel of American individuals, I present suggestive evidence that returns to net worth are heterogeneous and positively correlated with wealth. Then, I establish new dynamic empirical facts that propose wealthier individuals assumed to have information advantages earn higher returns after financial uncertainty shocks hit the economy. To interpret these facts, I build a heterogeneous-agent model in which households present some near-rationality behavior, which can be alleviated by receiving private information about future fundamentals. The model can match macro and financial moments in the data and the dispersion in forecast errors among professional forecasters. Using the model, I show that households with better information advantages can sustain higher net-worth returns. Then, I construct a model-based uncertainty measure similar to the one used in the empirical section. Using this measure, I show that better-informed households can better hedge against uncertainty shocks, resulting in higher relative returns to net worth. The model also suggests better-informed households are involved in a timing-the-market strategy by exploiting the fact that they receive more accurate information about future fundamentals.

Keywords: return heterogeneity, information frictions, financial uncertainty, heterogeneous-agent models
JEL Codes: E32, E44, E47, G17

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1. Introduction

During the last decades, there has been a significant increase in wealth inequality[1]. One explanation for this pattern is the existence of heterogeneous returns to wealth. Empirically, individual characteristics, such as managing a portfolio or identifying and accessing alternative investment opportunities, and portfolio characteristics, have explanatory power for the heterogeneity in returns[2]. However, there is no consensus on which of these two features is more important in explaining the observed heterogeneity in returns; and little is known about the dynamic patterns in the heterogeneous returns. Theoretically, a vast majority of studies propose exogenous process for heterogeneity in returns and calibrate them to match certain moments in the data[3]. In this paper, I propose a theory that links heterogeneity in returns to information frictions among investors. Using a panel of American individuals, I present suggestive evidence that net worth returns are heterogeneous and positively correlated with wealth. Then, I establish new dynamic empirical facts that propose that wealthier individuals assumed to have information advantages earn higher returns after an unexpected financial uncertainty shocks hit the economy. Then, I build a heterogeneous-agent model that highlights information frictions' role in explaining return heterogeneity and the heterogeneous effects of endogenous uncertainty on investors' performance.

The first part of the paper presents evidence that the cross-sectional dispersion of returns increases during recessions and remains high even when the recession ceases. This highlights that although the average cross-sectional performance decreases in recessions, there is significant heterogeneity across returns when a bad economic shock hits the economy (see Figure 2). This observation is challenging in standard macroeconomic models since higher uncertainty causes agents to tilt their portfolio towards the riskless asset, which has a lower standard deviation. Using the Panel Study of Income Dynamics (PSID), I construct portfolios at the individual level. The PSID offers aggregate measures of wealth and income that allow me to approximate returns to net worth. I find the following cross-sectional facts. First, returns to net worth are positively correlated with wealth. This positive correlation remains when I adjust the returns by the risk that investors face; that is, individual Sharpe ratio is also positively correlated with wealth. Adding to the existing empirical literature, I establish new empirical facts in a dynamic setting. I estimate a linear panel data model for individual returns to net worth and show that individuals who trade with more intensity and

[1] See Saez and Zucman (2016), Atkinson, Piketty, and Saez (2011), and Kuhn, Schularick, and Steins (2019)

[2] See Fagereng, Guiso, Malacrino, and Pistaferri (2020) and Bach, Calvet, and Sodini (2018) for empirical studies that highlight the importance of individual characteristics and portfolio exposure.

[3] See Gabaix, Lasry, Lions, and Moll (2016), Benhabib and Bisin (2018) Hubmer, Krusell, and Smith Jr (2019), and Benhabib, Bisin, and Luo (2019). Two studies that propose micro-founded models that generate heterogeneity in returns and satisfactorily match the wealth distribution are Quadrini (2000), in which entrepreneurial opportunities make wealthier household to save more, and Kaplan, Moll, and Violante (2018), in which a transaction cost in the higher return illiquid asset makes richer households to hold portfolios with higher returns

belong to the top 20% of the distribution earn, on average, 0.8% higher return with respect to individuals in the top 20% who do not declare trading activity, 3.0% higher return with respect to individuals in the bottom 80% without trading activity, and 3.9% with individuals in the bottom 80% who declare trading activity. Following the literature on attention and portfolio performance[4] I argue that the trading activity variable is a proxy for information advantage for individuals in the top 20%. I then study how trading behavior and the wealth distribution position affect portfolio performance when a bad shock hits the economy. In this sense, I aim to capture heterogeneous effects among individuals caused by informational disparities. To assess how returns for active-trading individuals respond to shocks, I interact the trading variable with Ludvigson, Ma, and Ng (forthcoming) estimate of financial uncertainty shocks. I then use Jordà (2005) local projection method to show that after an unexpected uncertainty shock, individuals that actively trade and belong to the top 20% earn, on average, around 0.3% more than individuals that do not trade and do not belong to the top 20% of the distribution. I also present evidence that this seems to result from a reallocation of the portfolio after the shock, which suggests a timing-the-market strategy.

To interpret these facts, as a start, I construct a static general equilibrium model of noisy rational expectation and endogenous information acquisition in which wealthy agents endogenously choose to be better informed about the future risky asset payoff. The model is qualitatively consistent with the cross-sectional facts observed in the data and highlights the potential importance of better information capacities in explaining returns heterogeneity. First, the model is consistent with the well-known finding that wealthier individuals have riskier portfolios. So, there is a level effect since wealthier individuals hold more units of capital. Besides, there is a composition effect since the model predicts that the share of risky assets in the portfolio is increasing in initial wealth. In terms of returns, the model shows that wealthier agents will spend more on information acquisition to get better signals about future payoffs, thereby generating a positive relation between ex-ante returns and wealth. The model also produces ex-ante Sharpe ratios increasing in wealth.

The static model provides two important insights, wealthier individuals acquire more information and hence obtain private signals with higher precision, and they hold more risky portfolios. Using these two observations, I propose a heterogeneous-agents model with informational frictions. In the model, two types of households coexist. Both receive private signals about the fundamental shocks in the economy; however, the signals' precision differs between them. For these frictions to have a role in the model, I assume that households are near-rational, and hence they cannot infer all information in the economy through prices or quantities. Households in the model can invest in two types of assets, capital and risk-free bond. Using the static framework insights, I calibrate the model such that the better-informed household holds a portfolio tilt toward the risky asset. The

[4] See Gargano and Rossi (2018).

model does a fair job matching macroeconomic and financial moments in the data. The model also matches some cross-sectional moments of portfolio holdings and the dispersion of forecast errors from the Survey of Professional Forecasters.

Using the model, I study the importance of informational frictions on the heterogeneity of returns. The model predicts a higher difference in returns to net worth and a higher cross-sectional dispersion between the better and worse-informed agents. Compared to an economy in which information frictions do not play any role, returns to net worth are higher in 34 basis points, and the dispersion is higher in 16 basis points. An important implication of the model is that the first autocorrelation of the return difference is 0.3 even though the same moment for excess returns is tiny. Reallocations in the share of the risky asset explain this persistence, which is a function of the difference in precision in the private signals. Then, and to relate the results with the empirical dynamic facts, I construct an endogenous measure of uncertainty following Ludvigson, Ma, and Ng (forthcoming). It is important to mention that my model does not feature stochastic volatility; hence, the uncertainty measure is based on the dispersion of forecast errors about the future price of capital. Using this measure, I show that the better-informed household can sustain higher returns for around four periods after an unexpected financial uncertainty shock. Besides, the model predicts that this household will adjust the composition of the portfolio by increasing the share in the risky asset when the price has decreased and then decreasing this share as the price recovers. Hence, the model suggests that better-informed households follow a timing-the-market strategy.

The rest of the paper is structured as follows. The following section places my contribution to the existing literature. Section 2 presents suggestive evidence on returns to net worth and the role of information in a dynamic setting. Section 3 proposes a simple static model and the quantitative model. Section 4 presents the results obtained from impulse response functions and simulations using the model. Finally, Section 5 concludes.

Related literature A vast literature aims to propose possible theories to explain the observed wealth inequality. On the theoretical side, the mechanisms that may account for skewness to the right and thick upper tails of the wealth distribution are skewed earnings (labor earnings or heterogeneity in the distribution of talents), idiosyncratic heterogeneous returns to net worth, and returns that covary positively with wealth[5]. Of these three potential explanations, heterogeneous returns and returns that covary positively with wealth (also referred to as explosive wealth accumulation process) are the ones that better match the observed wealth inequality in the data. However, the

[5]See, for instance, Hubmer, Krusell, and Smith Jr (2019), Benhabib and Bisin (2018), Benhabib, Bisin, and Zhu (2011), Benhabib, Bisin, and Luo (2017), Gabaix, Lasry, Lions, and Moll (2016), Cagetti and Nardi (2008), Castaneda, Diaz-Gimenez, and Rios-Rull (2003), Quadrini (2000), among others.

vast majority of studies take these mechanisms as exogenous and calibrate them to match the target inequality[6]. This paper proposes information frictions among individuals as a micro foundation to generate cross-sectional differences in returns.

On the empirical front, Fagereng, Guiso, Malacrino, and Pistaferri (2020), for Norwey, and Bach, Calvet, and Sodini (2018), for Denmark, present evidence that returns are heterogeneous; however, they disagree on the key drivers of this heterogeneity. TThe former argues that return heterogeneity is important. It not only arises from differences in the allocation of wealth and risk exposure, but it also reflects the heterogeneity in sophistication and financial information (this is captured by a fixed-effects estimator in their empirical model). The latter states that returns are determined by exposure to systematic risk and that factors such as informational advantages or exceptional investment skills are not significant drivers for the observed high returns of wealthy individuals. In the United States, Moskowitz and Vissing-Jørgensen (2002) study return to private and public equity, and Flavin and Yamashita (2002) analyses housing returns. My paper extends the analysis of these studies by jointly studying these asset categories and the liability side. This allows me to estimate returns to net worth. Then, I present two static facts and two new dynamic ones. TThe dynamic facts state that individuals who trade with more intensity obtain higher returns on average. This is potentially explained by a reallocation of the portfolio, suggesting a timing-the-market strategy. My paper is also related to the literature of uncertainty shocks (e.g. Bloom 2009, Jurado, Ludvigson, and Ng 2015, Ludvigson, Ma, and Ng forthcoming). I study how these type of shocks affect the first and second moment of returns.

My paper is also related to the empirical literature that aims to measure information advantages or attention in the data. Gargano and Rossi (2018) presents evidence that investors who spend more time in the brokerage account website doing research about their portfolio perform better. This paper also suggests that the proxies found in the literature, such as stocks trading volume and frequency, news, and analyst coverage, positively correlate with their measure of attention. I follow their lead and use trading frequency as a proxy for better informational advantages.

In the theoretical side, my paper relates to the literature that studies models of noisy rational expectations and information frictions[7]. In particular, Kacperczyk, Nosal, and Stevens (2019) study capital income inequality, whereas my paper focuses on heterogeneous returns. his paper

[6]Two papers that propose micro-founded models that generate heterogeneity in returns and satisfactorily match the wealth distribution are Quadrini (2000), in which entrepreneurial opportunities make wealthier household to save more, and Kaplan, Moll, and Violante (2018) in which a transaction cost in the higher return illiquid asset makes richer households to save at a higher rate.

[7]Papers of noisy rational expectations with endogenous information acquisition are Van Nieuwerburgh and Veldkamp (2006), Van Nieuwerburgh and Veldkamp (2010), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), among others.

also presents a static theory that cannot talk about the dynamic patters of heterogeneous returns to net worth that I found in the empirical section. Peress (2004) iis another static model that studies the interaction of wealth and information frictions. However, it neither study the effect of heterogeneous returns over the wealth distribution nor the dynamic response of returns to economic shocks. My paper contributes to the burgeoning literature on heterogeneous agent models. My paper extends the analysis in Hassan and Mertens (2014) and Hassan and Mertens (2017) by introducing households heterogeneous in the precision of their private signal and their portfolio composition. In this case, the wealth distribution is a state variable important in the analysis.

2. Empirical Evidence

In this section, I present suggestive evidence that wealthier individuals earn higher returns on average and that they can hedge better against negative economic shocks. I start describing the data I use to calculate returns to net worth. Then I present some facts for these returns and the portfolio of the individuals in the survey. In this paper, I argue that information frictions among individuals can potentially explain these facts. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) explain that it is challenging to measure the benefits of better information in the data directly. Hence, I follow the literature on information choice models suggesting to test the model's predictions on the data. Therefore, I present empirical results that can be rationalized with a model in which information frictions are a key ingredient to explain these facts.

2.1 Returns to net worth and portfolio composition

Data sources and return's definition: I use the PSID dataset for the period 1986 to 2017. PSID is a longitudinal household panel survey that began in 1968. The 1968 PSID sample was drawn from two independent sub-samples: an over-sample of around 2000 low-income families from the Survey of Economic Opportunity (SEO) and a nationally representative sample of about 3000 families designed by the Survey Research Center at the University of Michigan (SRC). Following Moskowitz and Vissing-Jørgensen (2002), I focus on the SRC sample, which was initially representative of the US population. Because of this, the PSID does not provide weights. The survey has information on demographics such as gender, age, marital status, years of education and degrees obtained, race, number of children, among others. It also provides geographics identifiers; in particular, it provides fips state codes for each household interviewed. The survey also provides wealth estimates of private business assets (W_{it}^{peq} where i denotes the individual and t the survey year), checking and savings (W_{it}^{cbs}), including checking or savings accounts, money market funds, certificates of deposit, government savings bonds, and treasury bills; stocks (W_{it}^{sto}), including stock in publicly held corporations, mutual funds, or investment trusts; IRA and private annuities (W_{it}^{ira}); house value (W_{it}^{hou}); other real estate assets (W_{it}^{ore}) excluding primary residence; and other assets (W_{it}^{oth}), including bond funds, cash value in a life insurance policy, a valuable collection for investment purposes, or rights in a trust or estate not already considered in any previous category. On the liability side, the PSID provides information about mortgage balances (D_{it}^{hou}), and other debts (D_{it}^{oth}), including credit card charges and student loans. Appendix B provides more information on the variables I use. I define gross financial, non-financial wealth and debt as follows

$$
\begin{aligned}
W_{it}^{fin} &= W_{it}^{cbs} + W_{it}^{sto} + W_{it}^{ira} + 0.5 * W_{it}^{oth} \\
W_{it}^{nof} &= W_{it}^{peq} + W_{it}^{hou} + W_{it}^{ore} + 0.5 * W_{it}^{oth} \\
D_{it}^{tot} &= D_{it}^{hou} + D_{it}^{oth}
\end{aligned}
$$

Note that W_{it}^{oth} includes financial components (such as bond funds, cash value in a life insurance policy) and non-financial components (like a collection for investment purposes, or rights in a trust or estate); for this reason, I split it equally between financial and non-financial wealth. Given these definitions, gross wealth and net wealth are

$$
\begin{aligned}
W_{it}^{\text{gross}} &= W_{it}^{fin} + W_{it}^{nof} \\
W_{it}^{\text{net}} &= W_{it}^{\text{gross}} - D_{it}^{tot}
\end{aligned}
$$

The survey gives information for the reference person and the spouse on income from unincorporated businesses (y_{it-1}^{peq}), rents (y_{it-1}^{rent}), interest (y_{it-1}^{int}), dividends (y_{it-1}^{div}), trust funds and royalties (y_{it-1}^{roy}), annuities (y_{it-1}^{ann}), income from IRAs (y_{it-1}^{ira}), Veteran's Administration pension (y_{it-1}^{VApen}), other retirement pays (y_{it-1}^{pen}), including other pensions, or annuities. For, imputed rent, the PSID asks about self-reported house rents of homeowners. However, this information is only present in the 2017 wave. Imputed rent is an important component of the income from the primary residence. Also, as highlighted by Cox and Ludvigson (2019), the price-rent ratio varied significantly during the last three decades (see Panel B of Figure 5). For this reason, I compute the ratio between rent and house value ($r_{is,2017}^{h}$) for homeowners i in state s in the last survey wave; then, I calculate the weighted (house value) average using properties with 2-12 rooms; finally, I apply the national grow rate of this ratio for the previous years. These ratios are used for the imputed rent ($\widehat{y}_{it}^{rent}$). The PSID does not provide information on stock capital gains (g_{it}^{sto}), which turns to be very important in explaining saving behavior across the distribution[8]. Without other sources to obtain a measure

[8]Fagereng, Blomhoff Holm, Moll, and Natvik (2019) use data Norwegian administrative panel data on income and wealth and show that saving rates net of capital gains are constant across the wealth distribution. Nevertheless, saving rates, including capital gains vary positively with wealth. They argue that wealthier households own assets that experience persistent capital gains and that they hold them in their portfolio instead of realizing the gains

of capital gains, I construct this variable as $g_{it}^{x} = W_{it}^{x} - W_{it-1}^{x}$. The PSID also includes information on mortgage payments, y_{it-1}^{mort}; however, it does not include information on payments on other types of debt such as credit card charges or student loans. For this reason, I use the Survey of Consumer and Finances (SCF) to approximate a measure of cost for this category. In particular, I construct a ratio of payments to debt balances along the distribution. Then I use this ratio on debt balances of the PSID to get the measure of pauments on other types of debt, I label this as y_{it-1}^{odebt}. It is important to note that all the income and cost of debt measures have a subscript $t-1$, this is because the PSID asks about income and cost of debt on the previous year. The measures of financial and non-financial income and cost of debt are

$$\begin{aligned}
y_{it}^{fin} &= \left(y_{it}^{div} + g_{it}^{sto}\right) + \left(y_{it}^{int} + y_{it}^{roy} + y_{it}^{pen} + y_{it}^{ann} + y_{it}^{ira} + y_{it}^{open}\right) \\
y_{it}^{nof} &= \left(\widehat{y}_{it}^{rent} + g_{it}^{hou}\right) + \left(y_{it}^{rent} + g_{it}^{ore}\right) + \left(y_{it}^{bus} + g_{it}^{peq}\right) \\
y_{it}^{debt} &= y_{it}^{mort} + y_{it}^{odebt}
\end{aligned}$$

Net income is defined as follows

$$y_{it}^{net} = y_{it}^{fin} + y_{it}^{nof} - y_{it}^{debt}$$

I will work with the definition of returns used in Fagereng, Guiso, Malacrino, and Pistaferri (2020), which applies the methodology presented in Dietz (1968). The estimate of the realized return to a given asset class is the flow of annual income generated by the asset class over the value of the asset class at the beginning of each period, adjusting for intra-year asset purchases and sales. Therefore, I need estimates of both flows and stocks of the particular asset class. The return to net worth, which is the key concept in the analysis I present here, is

$$r_{it}^{nw} = \frac{y_{it}^{net}}{W_{it}^{\text{gross}} + 0.5 * F_{it}^{\text{gross}}} \tag{1}$$

where F_{it}^{gross} accounts for the fact that asset yields may be generated by additions/substractions of assets during the year. In particular, for the asset class k, it is defined as the difference in initial and end-of-period period wealth minus the income that is capitalized into end-of-period wealth

$$F_{it}^{k} = \Delta W_{it+1}^{k} - \tilde{y}_{it}^{k}$$

where $\tilde{y}_{it}^{k}$ is specific to the asset type, with $k \in \{sto, csb, hou, ore, peq\}$. I impose some selection requirements to reduce errors in the estimated of returns to net worth. In particular, I focus on individuals between 20 and 75 years old. Besides, I consider individuals with a financial wealth of at least \$ 500 and individuals with a non-zero private business wealth of at least \$200. Finally, I trim the distribution of returns in each year at the top and bottom 0.5%. Note that to construct the measures of return, one need the beginning-of-period and end-of-period wealth. The PSID supplements wealth every two years since 1999. Before that, the publication of wealth measures was even more sparse. For this reason, I really on linear interpolation to obtain wealth measures for missing years. I conduct more finer approaches in which I take into account the price dynamics of each asset in the portfolio and obtain similar results.

Table 1 presents summary statistics for several waves of the PSID. Wealth variables are at the household level. Income variables are at the reference person and spouse level. In the wealth variables, I split them equally for households with reference person and spouse. Next, I present facts on returns to net worth obtained using the PSID data. Some of these facts are already mentioned in the literature for the United States and other countries[9].

Cross-section average and standard deviation of returns to net worth and portfolio composition: Table 2 presents returns for different asset categories. The average net worth return during the sample period (1986 - 2007) was 2.1%, and its standard deviation was 19%. In the case of financial wealth, the average return was 5.2%, and its dispersion 20%. As expected, the dispersion of the risky assets (stocks, mutual funds, IRAs, among others) is higher. Non-financial wealth return was 8%, with a dispersion of 38%. These numbers suggest that returns to net worth present a significant cross-sectional dispersion, and this is mainly driven by stocks, housing, and private business. A concern may arise because the PSID does not track the very top of the distribution as, for example, the SCF does. Pfeffer, Schoeni, Kennickell, and Andreski (2016) explain that the PSID and the SCF provide similar estimates for wealth up to the top 2-3%. This could be a problem for my hypothesis that wealthier households have informational advantanges that allows them to obtain higher returns to net worth. In any case, my results provide a lower bound if I were to include the very top of the distribution. Moreover, as suggested by Smith, Zidar, and Zwick (2019), once one accounts for heterogeneity within asset classes when mapping income flows to wealth when using the capitalization approach in Saez and Zucman (2016). It is the 90-99th percentile that holds more wealth than the other percentiles of the distribution. This group, as suggested by Pfeffer, Schoeni, Kennickell, and Andreski (2016) is equivalent in the PSID and the SCF.

Table 3 presents the portfolio composition across the distribution of net worth. It is important to note that the portfolio of the bottom 50% is concentrated in private residences and safe assets (checking, saving accounts, and bonds, CSB). Also, these individuals are highly levered. As individuals move to the upper section of the distribution, stocks and private equity become more

[9] for US, Moskowitz and Vissing-Jørgensen (2002) provides measures of private business return and public return. Also Flavin and Yamashita (2002) provides returns for housing. For Norwey, Fagereng, Guiso, Malacrino, and Pistaferri (2020) and for Sweden Bach, Calvet, and Sodini (2018) provide measures of returns for different asset classes.

important. Housing and CBS assets are still important, but their share decreases as wealth increases. This table is in line with previous studies that show how wealthier individuals tilt their portfolio towards risky assets. In the model I present below, I do not explicitly model the housing market. Instead, I group into capital the holdings of stocks, housing, and private business in the calibration. However, as one moves up in the distribution, individuals hold positions in riskier assets remains if one considers just renters. Table 3b presents the portfolio composition for renters in the survey. Renters account for around 30% of the households in the PSID (see Table 1). As the Table suggests, individuals in the lower part of the distribution hold a higher share in CSB. As one moves up in the distribution, stocks and private business wealth become more important. The fact that households in the bottom 50% of the distribution hold shares in stocks come from the fact that this measure includes IRA.

Cross-sectional average returns and Sharpe ratios across the wealth distribution: The upper panel of Figure 1 presents the cross-sectional average and median returns to net worth for agents in different percentiles of the wealth distribution for the entire sample (1986-2017). This figure suggests a positive correlation between returns with net worth. In particular, individuals below 25% earn negative returns to net worth because they are high leveraged, and the cost of debt is higher than the financial and non-financial income they get. This fact is a key fact since Benhabib, Bisin, and Luo (2019) argue that this positive correlation is important to match the thick upper tail of the wealth distribution. The fact that wealthier individuals earn higher returns result from their portfolios been tilt towards riskier assets. A more accurate measure of profitability in investment decisions should then consider the implicit risk that these individuals face. Panel (b) of 1 presents a measure of Sharpe ratio which is calculated as $SR_i = \frac{\sum_{t_i=1}^{N_i}\left(r_{it}^{nw}-\bar{r}_i^f\right)}{\sqrt{\sum_{t_i=1}^{N_i}\left(r_{it}^{nw}-\bar{r}_i^{nw}\right)^2}}$, where r_{it}^{nw} is the return to net worth of individual i in period t and $\bar{r}_i^{nw}$ is the average risk-free rate (three-month treasury bill rate) for the investment horizon. Note that this measure takes into account the risk in the individual portfolio. As the Panel shows, there is a positive relationship between the Sharpe ratio and the wealth distribution. This suggests that even when adjusting for the individual portfolio risk, a wealthier individual obtain higher returns.

2.2 Dynamic patterns of returns

The preceding section discussed cross-sectional static facts of returns to net worth. In this section, I study the dynamic patterns of returns. Panel (a) of Figure 2 presents the cross-sectional average and cross-sectional dispersion of returns to net worth over the sample period. The asset pricing literature highlights that recessions increase the volatility of returns and decrease the average of them (see Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016)). The same pattern is observed when computing returns to net worth using the PSID. As the figure shows, cross-sectional average returns have decreased in all recessions over the sample period. Moreover, the cross-sectional dispersion of returns increases during these recesions and remains high even after the recession ceases.

In this paper, I study the dynamic effect of economic shocks on returns. Panel (b) shows a measure of financial uncertainty shocks borrowed from Ludvigson, Ma, and Ng (forthcoming). Note that uncertainty has a negative correlation with cross-sectional average returns which suggests that during periods of high financial volatility investors' perform worse. In this study, I argue that information frictions, in an environment of noisy private signals, partially explain these facts. In addition, I show that bad economic shocks; for instance, uncertainty shocks, affect investors differently; and that wealthier investors, considered better-informed and with better investment opportunities (through mutual funds, hedge funds, or financial advising) can perform better when confronted to these bad shocks.

As I mentioned before, it is challenging to find a correct measure of information disparities across invertos in the data. There are a few empirical studies that construct direct measures of attention across investors. Gargano and Rossi (2018) use a novel brokerage account data set to construct measures of attention based on the number of seconds that investors spend on brokerage account website, the total number of research pages visited by the investor while in the brokerage account website, and the numbers of logins to the brokerage account website. They find a strong positive cross-sectional correlation between their measures of attention and portfolio performance. They also find positive correlation between their measures of attention and other proxies used in the literature, such as stocks trading volume and frequency, news, and analyst coverage with trading frequency being the most economically and statistically significant. In the theoretical side, Kacperczyk, Nosal, and Stevens (2019) show that better-informed agents adjust the size and the composition of their portfolios towards risky assets. So, one can argue that these agents will trade more intensively in, for instance, public equity or stocks.

Starting in the 1989 wave, the PSID asks respondents several question regarding portfolio rebalances. In particular, I am interest in the following question: *Since the previous survey, did [you/you or anyone in your family living there/they] buy or sell any shares of stock in publicly held corporations, stock mutual funds, or investment trusts, including any automatic reinvestments – not including any IRAs?* And the respondents may answer yes bought, yes sold, yes both, or no. Following the evidence in Gargano and Rossi (2018) and Kacperczyk, Nosal, and Stevens (2019), I will use the *yes* answer in this variable as a proxy for better-information advantages among individuals.

Figure 3 presents the fraction of respondents in each survey wave that belong to the top 10% and 20% of the distribution. As the figure suggests, wealthier individuals explain almost 50% of the reported trading activity in the PSID. In the quantitative section of this article, I present a simple static model that highlights the positive relationship between wealth and information acquisition. So I bring that insight to the empirical section and suggest that these actively trading investors have better informational advantages over other individuals in the survey.

To study the effect of trading behavior on returns' performance, I first estimate a linear panel data model of the returns to net worth. The general specification of the empirical model is the following

$$r_{it}^{nw} = X_{it}'\beta + u_{it} \tag{2}$$

where r_{it}^{nw} is the return to net worth of individual i in period t. X_{it} is a vector of covariates with three set of variables. The first set includes demographic variables such as age, education, gender, and race. The second one includes portfolio characteristics such as the share of the portfolio in CBS, stocks, housing, private business, and debt. These variables are included to model the observable risk exposure. To avoid potential endogeneity problems, I use shares at the beginning of the period. The last set of variables includes measure to control for scale using the position of each individual in the wealth distribution, time effects, and regional effects.

Table 4 presents the results. The first column shows the results for the model in (2). The model controls for demographics, year, and state effects. As expected, shares in the portfolio are significant and with the correct sign. In particular, the model predicts that an individual with an additional one percent of wealth allocated in public equity can earn, on average, a 3% higher return to net worth. The interpretation of the other asset classes is equivalent. In the case of debt, an additional one percent of leverage causes the return to decrease in around 3%. This evidence is consistent with other studies that study the determinants of returns to net worth (see for instance Fagereng, Guiso, Malacrino, and Pistaferri (2020)).

The second column, includes a measure of financial uncertainty discussed with more detail below. This measure suggests that an increase in 1% on the financial uncertainty shock generates a decrease of 4.1% in the return to net worth. In the last column I add three new variables. The first one defines individuals in the top 20% of the distribution that declare not to adjust the portfolio in stocks from the previous survey. The second and third variables considers individuals in the bottom 80% of the distribution that do not adjust and that adjust, respectively. Therefore, these variables gives the effect compared to the individuals in the top 20% of the distribution who declare to adjust the portfolio in stocks since the previous survey. These results suggest that wealthier individuals not trading earn on average -0.8% lower returns with respect to the wealthier individuals trading. If the individuals belongs to the bottom 80%, they earn -3.0% if they do not trade and -3.9% if they trade with respect to wealthier individuals who trade. Note that for the bottom 80% of the distribution these results are in line with the studies suggesting that individuals who trade too frequently perform worse than investors not trading as often[10].

The previous analysis consider potential determinants of returns to net worth on a static framework. The following set of results study the dynamic patterns of returns to net worth. In particular, I show that wealthier individuals who adjust the portfolio between surveys have better performance when a bad shock hits the economy. I use a measure of financial uncertainty shocks provided by Ludvigson, Ma, and Ng (forthcoming). These authors construct macroeconomic and financial uncertainty indexes using the methodology of Jurado, Ludvigson, and Ng (2015). Then, they estimate a three-variable structural VAR that includes both uncertainty indexes and a measure of real economic activity. Then, they obtain the residuals from the structural VAR and these are the shocks. Figure 4 panel (a) presents the uncertainty shock at a monthly frequency while panel (b) shows it at the annual frequency. Since my estimates are for yearly returns to net worth, I focus on the latter.

I use this shock and interact it with the active-trading variable discussed above. I then estimate a forecasting model for the return to net worth following Jordà (2005) local projection method. Specifically, I estimate the following regression

$$r^{nw}_{it+h} = \alpha_h + X'_{it}\beta_h + \gamma_h \left(\mathrm{e}^F_t \ \# \ \text{active trading}_{it}\right) + u_{it+h} \tag{3}$$

for $h > 1$. e^F_t is Ludvigson, Ma, and Ng (forthcoming) financial uncertainty shock and X_{it} contains the variables discussed above, including the active trading variable. I do not include the shock itself in X_{it} because of the time-effects in the model. Figure 5 shows the estimate of γ_h for $h > 0$. In panel (a), I estimate the model without including any of the covariates in X_{it}. This graph suggests that investors who actively trade and belongs to the top-20 of the wealth distribution perform better (0.3% higher returns) for around four periods after the shock. Panel (b) presents the results of the same exercise but adding the other covariates. Both models predict almost the same response.

In the above discussion, I argue that a proxy for informational advantages between individuals is the trading variable. If this is the case, one would expect that the observed dynamic response on returns in Panel (a)-(b) is the result of some rebalance of portfolio. Then, I estimate a model similar to that in 3 but with the share on stocks as the left-hand side variable. The results of this regression are in Panel (c)-(d) of Figure 5. The results suggest that after an unexpected financial uncertainty shock, individuals in the top 20% of the distribution who declare trading activity, increases the share in stocks and then reduce it once stock prices start to recover. This behavior suggests a

[10] See for instance Odean (1998) and Barber and Odean (2000)

timing-the-market strategy. The individuals buy stocks when the prices are depressed and then sell them once the price start to recover potentially realizing the capital gains and hence obtaining higher expected returns.

3. Quantitative Analysis

In this section, I present a simple static model that links information advantages with initial wealth. The model can qualitatively explain the static facts presented in the empirical section. Also, this model suggests that wealthier individuals earn higher returns and tilt their portfolios toward the risky asset. I use this two insights in a dynamic model. I investigate the quantitative implications of uncertainty shocks in a model with dispersed information. I start by extending the static model to an infinite horizon setup. The model is a standard real business cycle framework with Epstein and Zin (1989) preferences and long-run productivity shocks in the spirit of Croce (2014). As in the static model, the dynamic framework features two production sectors. The first one produces the final good in the economy and the second one produces the physical capital. Following Hassan and Mertens (2017), I include dispersed information among agents. In particular, there are two sets of agents that receive private signals about the productivity shocks. These sets of agents differ in the precision of the private signal they get. To highlight the role of dispersed information, I simplify the model's heterogeneity by aggregating the two sets of agents into two representative households. Both households trade in the stock market and in debt markets and only differ in the quality of information they receive about the economy's fundamental shocks. I calibrate the model so that one of the households issues bonds to finance its investment opportunities, and the second one purchases this debt. In the static model, I show that wealthier individuals acquire signals with higher precision. I use this insight in the dynamic model by assuming that the wealthier representative household has a private signal with better precision.

3.1 Insights from a static model

Setup: I build a standard endogenous information acquisition model[11] with a realistic production sector to relate the results to the dynamic model. The model presents a measure of investors that, depending on their wealth holdings, are able to acquire information to have a better prediction of capital payoff. There are two types of production sectors, an investment good sector which supply capital (k) subject to adjustment costs, and a final good sector which uses capital to produce the final consumption good (y). The final good sector owns the investment sector. The model economy

[11] The model is similar to the one in Verrecchia (1982) and Peress (2004).

exists at three periods. In the first period (planning period), each agent chooses the precision of signal about the capital payoff subject to an increasing cost for more precise information. In the second period (trading period), each agent observes her private signal and the price and decides its portfolio allocation. In the last period, each agent receives the capital payoff and realizes her utility. Figure 6 presents the timing of the model.

In the planning period, an endowment of a numéraire good can be stored until the last period or converted into k units of capital at adjustment cost $\frac{1}{2\kappa}k^2$ with $\kappa \geq 0$ and fixed cost ψ. The investment good sector that performs instant arbitrage between the price of capital (q) traded in a competitive stock market during the trading period and the number of units of capital in circulation:

$$\pi = \max_k \left\{ qk - k - \frac{1}{2\kappa}k^2 - \psi \right\}$$

The first-order condition of this problem determines the supply of capital in the economy

$$k = \kappa \left(q - 1 \right) \tag{4}$$

There are two assets in the economy, a riskless asset (bonds) and a risky asset (units of capital). The riskless asset is in perfectly elastic supply and its price is set to $p^f = 1$ and its gross return $R^f = 1 + r^f$. The payoff of the per unit of the risky asset is given by $\eta = \bar{\eta} + \epsilon_\eta$ with $\epsilon_\eta \sim N(0, \sigma_\eta)$. Hence, an agent that purchases k units of capital in the trading period will realize a payoff ηk. As is standard in noisy rational expectation models, to prevent the capital price from fully revealing the information and hence discourage the acquisition of private information, I include a random supply for capital emanating from noise traders, this group of agents trade for reasons not explained in the model. Noise traders supply follows a normally distributed process $\theta \sim N\left(0, \sigma_\theta\right)$. In the dynamic model, I assume near-rationality as a device to prevent prices to fully reveal all the information because this allow me to compare the results with respecto to an economy in which information frictions do not play any role.

Agents i can spend resources acquiring information about the capital payoff η. In practice, the agent pays a variable cost to set the level for the precision (inverse of the variance) of its signal. Each receives a signal s_i which is an unbiased estimator of the capital payoff

$$s_i = \eta + \epsilon_i \tag{5}$$

$\{\epsilon_i\}$ is independent of η, θ, and is independent across agents. I assume a normal distribution for this disturbance; that is, $\epsilon_i \sim N(0, x_i^{-1})$ where x_i is the precision or the inverse of the signal's variance, i.e. $x_i^{-1} = \sigma_i$. Agents inccur in costs when acquiring information. This cost is given by $C(x_i)$. The function $C(\cdot)$ is increasing and strictly convex in x_i. I impose the following restrictions on $C(\cdot)$: $C(0) = 0$, $C'(\cdot) \geq 0$, $C''(\cdot) > 0$ on $[0, \infty]$, and $\lim_{x\to\infty} C'(x) = \infty$. These assumptions imply an interior solution for the problem.

There is a unitary mass of heterogeneous agents. Heterogeneity in this case is in initial wealth W_{0i}. In general, the household utility will be given by $U_{0i} = \mathbb{E}_0[U_{0i}(\mathbb{E}_{1i}[u_1(W_1)])]$, define $U_{1i} = \mathbb{E}_{1i}[u_1(W_1)]$. Agents' objective is to maximize expected utility of terminal wealth W_{1i}. I define the absolute risk tolerance by $\Gamma(W_1) \equiv -\frac{u_1'(W_1)}{u_1''(W_1)} = \frac{W_1}{\rho}$ with $u_1 = \frac{1}{1-\rho} W_1^{1-\rho}$. Let Λ be the cumulative joint distribution function of W_{0i} on a compact set $[\mathcal{W}_0, \overline{\mathcal{W}}_0]$. Then, define a measure of agents' aggregate risk tolerance by $\Gamma \equiv \int_i \Gamma(W_{0i}) d\Lambda(W_{0i})$.

Solution: The model is solved in two steps. In the first one, which corresponds to the trading period, the agent observes the price of capital q and the private signal s_i and decides her portfolio taking as given q, the riskless return $R^f = 1 + r^f$, and the precision level. In the second step, which corresponds to the planning period, the agent chooses the precision for the private signal x_i. The details of the derivation are in Appendix A.1. There are three types of information that aggregate in posterior beliefs, the prior beliefs, the information in the capital price, and the private signal. Using Bayes' law, the posterior mean and variance of η given the information obtained from the private signal and the price are

$$\mathbb{E}_{1i}[\eta] = \mathbb{E}_i[\eta | s_i, q] = \mathbb{V}_{1i}[\eta] \left(\sigma_\eta^{-1} \bar{\eta} + x_i(W_{0i}) s_i + \sigma_q^{-1} \tilde{q} \right) \tag{6a}$$

$$\mathbb{V}_{1i}[\eta] = \mathbb{V}_i[\eta | s_i, q] = \left(\sigma_\eta^{-1} + x_i(W_{0i}) + \sigma_q^{-1} \right)^{-1} \tag{6b}$$

where $\tilde{q}$ is an unbiased estimator of the public signal (q) and $x_i'(W_{0i}) > 0$. Note that the conditional variance is a decreasing function of the private signal precision. Hence, an agent acquiring more information is able to reduce the conditional variance of payoff. I define the number of units of capital in the portfolio with z_{1i} and the share of stock on agent i's portfolio with α_{1i}. Then, the ex-ante optimal portfolio holdings and shares are

$$\mathbb{E}[z_{1i}] = \frac{W_{0i}}{\rho} \mathbb{E}\left[\frac{\mathbb{E}_{1i}[\eta] - qR^f}{\mathbb{V}_{1i}[\eta]} \right] \qquad \mathbb{E}[\alpha_{1i}] = \frac{1}{\rho} \mathbb{E}\left[q \left(\frac{\mathbb{E}_{1i}[\eta] - qR^f}{\mathbb{V}_{1i}[\eta]} \right) \right] \tag{7}$$

In addition, I obtain a measure for ex-ante returns to net worth and Sharpe ratio

$$\mathbb{E}[r_i^n] = \mathbb{E}\left[\alpha_{1i} \left(\frac{\eta - q}{q} - r^f \right) \right] + r^f \qquad \mathbb{E}[SR_i] = \frac{\mathbb{E}[r_i^n] - r^f}{\mathbb{V}[r_i^n]} \tag{8}$$

Figure 7 presents a graphic representation of the expressions above as a function of the inital wealth. Consistent with the static facts presented in the empirical section, the model suggests that wealthier individuals tilt their portfolio toward the riskier asset (see Panel a). This is expected since the wealthier the individual the higher the number of units of capital she will have in her portfolio. Nevertheless, Panel (b) shows that the share of the risky asset in the portfolio is also increasing in wealth. Hence, wealthier individuals will allocate more wealth towards the risky asset. Panel (c) shows that in a model with information frictions, wealthier agents will acquire more information and that will result in higher expected returns. This pattern remains even when one controls for the risk of the individual portfolio, Panel (d) presents the ex-ante Sharpe ratio. These four graphs suggests that a model with information frictions can rationalize the empirical facts presented in the previous section.

3.2 Quantitative model

Production sector

Final good sector: The final good producer uses capital and labor to produce the consumption good using a linear homogenous production function

$$y_t = k_{t-1}^{\alpha} \left(z_t l_t \right)^{1-\alpha} \tag{9}$$

where y_t is the output of the consumption good, k_{t-1} is the beginning-of-period t aggregate physical capital, z_t is labor productivity, and l_t is aggregate labor. I assume that productivity is characterized by a non-stationary process with a growth rate that follows

$$\Delta z_{t+1} = \mu + \omega_t + \sigma_S \eta_{t+1}^S \tag{10}$$

productivity growth has a long-run component ω and a short run component η^S. The long-run component follows an autoregressive process of order one given by

$$\omega_t = \rho \omega_{t-1} + \sigma_L \eta_t^L \tag{11}$$

$\{\eta^S, \eta^L\}$ are assumed to be independent, normally distributed with mean zero. The agents will receive private signals about the future realization of the long-run (η^L) and short-run (η^S) components and these private signals will be the source of dispersed information in the model. The final good producer will rent capital and pay for labor services from the household sector. Given that the final good producer does not make any investment decision and it only rents services from an existing capital stock, its problem becomes the standard period-by-period maximization problem

$$\Pi_t^F = \max_{k_{t-1}, l_t} \; y_t - r_t^k k_{t-1} - w_t l_t \tag{12}$$

where k_{t-1} is the capital demand and l_t the labor demand. The first-order conditions of this problem define the wage and the rental rate of capital

$$w_t = (1-\alpha) \frac{y_t}{l_t} \tag{13a}$$

$$r_t^k = \alpha \frac{y_t}{k_{t-1}} \tag{13b}$$

Since the production function is Cobb-Douglas, the final good producer makes zero economic profits from producing the consumption good. Therefore, the only source of non-labor income that the firm produces is the rental rate of capital r^k.

Capital investment sector: The second firm in the economy is the capital investment firm. The final good producers own this investment firm, which produces physical capital in the economy, paying quadratic adjustment costs. The firm takes the price of capital as given and then seeks to maximize profits

$$\widetilde{\Pi}_t^x = \max_{x_t} \; q_t \left(x_t - \Psi \left(\frac{x_t}{k_{t-1}} \right) k_{t-1} \right) - x_t \tag{14}$$

where q_t is the price of capital, x_t is an investment in units of the final good, and $\Psi\left(\frac{x_t}{k_{t-1}}\right)$ are the adjustment costs to capital that take the specification proposed by Jermann (1998)

$$\Psi\left(\frac{x_t}{k_{t-1}}\right) = \frac{x_t}{k_{t-1}} - \left(\frac{\nu_1}{1-\frac{1}{\xi}} \left(\frac{x_t}{k_{t-1}} \right)^{1-\frac{1}{\xi}} + \nu_0 \right) \tag{15}$$

ξ determines the equilibrium elasticity of the capital stock with respect to the stock price. ν_1 and ν_2 are two positive parameters. These parameters are chosen such that adjustment cost and its derivative are zero in the deterministic steady-state of the stationary economy (where variables are detrended to ensure a balanced growth path)

$$\begin{aligned} \nu_1 &= (\delta + e^{\mu} - 1)^{\frac{1}{\xi}} \\ \nu_0 &= \frac{1}{1-\xi} (\delta + e^{\mu} - 1) \end{aligned}$$

Taking the first-order condition of the problem in (14), one obtains the equilibrium price of capital

$$q_t = \frac{1}{1 - \Psi'\left(\frac{x_t}{k_{t-1}}\right)} \tag{16}$$

Different from the case of the final good producer, due to decreasing returns to scale in converting consumption goods to capital, the investment sector gets positive profits each period that amount to

$$\widetilde{\Pi}_t^x = q_t \left(\Psi'\left(\frac{x_t}{k_{t-1}}\right) x_t - \Psi\left(\frac{x_t}{k_{t-1}}\right) k_{t-1} \right)$$

hence, profits per-unit of capital stock k_{t-1} are

$$\pi_t^x = \frac{\widetilde{\Pi}_t^x}{k_{t-1}} = q_t \left(\Psi'\left(\frac{x_t}{k_{t-1}}\right) \frac{x_t}{k_{t-1}} - \Psi\left(\frac{x_t}{k_{t-1}}\right) \right) \tag{17}$$

The production sector collects the revenue from the rental rate of capital that the final good producer pays and profits per-unit of capital from the investment firm and pays them as dividends to the households. The dividends per unit of capital are

$$d_t = r_t + \pi_t^x \tag{18}$$

Finally, the stock of capital evolves according to the following law of motion

$$k_t = (1-\delta)\, k_{t-1} + x_t - \Psi\left(\frac{x_t}{k_{t-1}}\right) k_{t-1} \tag{19}$$

where δ is the capital depreciation rate.

Household sector

Information structure: I start by presenting the agents' information structure in the model and the aggregation into representative households. The economy is populated by a continuum of agents that receive private signals about fundamental shocks $\{\eta^S, \eta^L\}$. As I mentioned above, these agents belong to one of two groups. The first group receives private signals with higher precision and is labeled as better-informed agents. The second group is composed of worse-informed agents.They receive private signals with lower precision (or higher variance). I make assumptions that allow me to aggregate these agents into representative households. I follow this approach to reduce the heterogeneity that arises from the realization of the private signals among agents. The first representative household has a measure λ. This is the better-informed household and is composed by the group of agents who receive the "informative" private signals, one for the long-run productivity component η^L_{t+1} and the other one for the short-run productivity component η^S_{t+1}. The second representative household is composed by the worse-informed agents, it is refered as the worse-informed household and it has a measure $1-\lambda$.

In the model, better-informed and worse-informed agents differ in the quality of the private signals they receive about the next period long and short-run productivity shocks. Let $j = \{i, u\}$ label agents in the first group (i for better-informed) and the second group (u for worse-informed); hence, the private signals are given by

$$s^L_{jt} = \eta^L_{t+1} + \sigma^L_j\, \epsilon^L_{jt} \tag{20a}$$

$$s^S_{jt} = \eta^S_{t+1} + \sigma^S_j\, \epsilon^S_{jt} \tag{20b}$$

where ϵ^L_{jt} and ϵ^S_{jt} are disturbance shocks distributed as standard normal processes. Agents in the model observe all prices and aggregate state variables at time t and understand the structure of the economy, as well as the equilibrium mapping of information into prices and economic aggregates. This implies that the rational expectation operator will be different for the better-informed and worse-informed agents. In particular, the rational expectations for these two types of agents will be as follow

$$\mathbb{E}_{it}\left[\cdot\right] = \mathbb{E}\left[\cdot|\, s^L_{it},\, s^S_{it},\, q_t,\, q^f_t,\, d_t,\, w_t,\, c_t,\, l_t,\, k_{t-1},\, y_t,\, x_t,\, \Psi_t,\, \Delta z_t,\, \omega_{t-1}\right] \tag{21a}$$

$$E_{ut}\left[\cdot\right] = \mathbb{E}\left[\cdot|\, s^L_{ut},\, s^S_{ut},\, q_t,\, q^f_t,\, d_t,\, w_t,\, c_t,\, l_t,\, k_{t-1},\, y_t,\, x_t,\, \Psi_t,\, \Delta z_t,\, \omega_{t-1}\right] \tag{21b}$$

where q_t^f is the price of the bonds, and c_t is the aggregate consumption. The only sources of uncertainty in the model are η_{t+1}^L and η_{t+1}^S and households form conditional expectations of them using the information sets in (21). For differences in the quality of information to have a role in the model, I need to assume that public signals; that is, the prices and aggregate quantities in the economy, do not reveal all the necessary information that agents need to form expectations. For this reason, I follow Hassan and Mertens (2017), and I assume that households make small common errors when forming their expectations. These errors shift the posterior probability density of the short and long-run productivity shocks by a common factor ε. Therefore, the expectation operator for each type of agents is the sum of the rational expectation operator in (21) and the common error shock

$$\mathcal{E}_{jt}\left[\eta_t^k\right] = \mathbb{E}_{jt}\left[\eta_t^k\right] + \varepsilon_t^k \qquad k = \{L, S\} \tag{22}$$

where $\varepsilon_t^k \sim N(0, \sigma_{\varepsilon k})$ with $k = \{L, S\}$; that is, the common errors have the same distribution across informed and uninformed households. The fact that agents receive signals about the future long and short-run probability shocks result in a distribution of choice and state variables that generates a non-degenerate distribution of wealth at the end of every period among each household type. To avoid tracking this distribution, at the beginning of every period individuals within each household group trade claims (H_{jt}) that are contingent on the state of the economy and the realization of the noise they receive in their private signals ϵ_{jt}^k for $k = \{L, S\}$ and $j = \{i, u\}$. These claims, which are in zero net supply within each representative household, pay off at the beginning of the following period. A fundamental assumption is that these claims are traded before any information about the shocks is revealed. This implies that the prices of these claims do not have any information about future productivity shocks. In equilibrium, individuals in each household type choose to hold these securities which payoff is given by

$$H_{jt} = \begin{cases} \lambda q_{t-1} R_{t-1} k_{t-1} - (q_{t-1} R_{t-1} k_{jt-1} + b_{jt-1}) & \text{if } \{c_{jt}, l_{jt}, k_{jt}, b_{jt}\} = \arg\max (23)|_{H_{jt}=0} \\ 0 & \text{otherwise} \end{cases}$$

The fact that there is perfect risk sharing among household types allows me to present all the analysis that follows in terms of a representative household within each household. Hence, I will refer to these agents as the better-informed and worse-informed households.

Preferences and budget constraints: Households have Epstein and Zin (1989) preferences over consumption and leisure. Let $v_{jt}(S_t, k_{jt-1}, b_{jt-1})$ be the value function of a household j that starts the period t with an aggregate state S_t (described below) and individual states $\{k_{jt-1}, b_{jt-1}\}$. I follow Croce (2014) by assuming that consumption and leisure are complements

$$v_{jt}(S_t, k_{jt-1}, b_{jt-1}) = \left((1-\beta)\, \tilde{c}_{jt}^{1-\frac{1}{\psi}} + \beta \mathcal{E}_{jt} \left[(v_{jt+1}(S_{t+1}, k_{jt}, b_{jt}))^{1-\gamma^j} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma^j}} \right)^{\frac{1}{1-\frac{1}{\psi}}} \tag{23}$$

where ψ and γ^j measure the agents' intertemporal elasticity of substitution and relative risk aversion, respectively. The consumption bundle $\widetilde{c}_{jt}$ is a Cobb-Douglas aggregator of consumption and leisure

$$\tilde{c}_{jt} = c_{jt}^{\chi} \left(z_{t-1} \left(1 - l_{jt}\right)\right)^{1-\chi} \tag{24}$$

since the model is not stationary because of the productivity process, leisure needs to scale with labor productivity to ensure the existence of a balanced growth path. Households get funds from labor, holdings of capital, and holdings of bonds. They use these funds to finance consumption and their demands for capital and bonds. Let ws_{jt} denote the wealth share of household j, which is given by

$$\mathrm{ws}_{jt} = \lambda_j \frac{q_{t-1} R_t k_{jt-1} + b_{jt-1}}{q_{t-1} R_t k_{t-1}} \tag{25}$$

where the return on capital holdings R_t is given by

$$R_t = \frac{d_t + (1-\delta) q_t}{q_{t-1}} \tag{26}$$

The above analysis implies that the budget constraint for household j is given by

$$c_{jt} + q_t k_{jt} + q_t^f b_{jt} + \Psi_j^b(b_{jt}) = w_t l_{jt} + n_{jt-1} + T_{jt} + H_{jt} \tag{27}$$

with beginning-of-period wealth given by

$$n_{jt-1} = \frac{1}{\lambda^j} \mathrm{ws}_{jt} q_{t-1} R_t k_{t-1}$$

for $j = \{i, u\}$. In addition, and as it is standard in models with portfolio choice problems, to obtain a well-defined deterministic steady state, I include a tiny bond holding cost function $\Psi_j^b(b_t^j)$ with

$$\Psi_j^b\left(b_{jt}\right) = q_t^f z_t \frac{\psi_j^b}{2} \left(\frac{b_{jt}}{z_t} - b_{jss}\right)^2 \tag{28}$$

T_{jt} are transfers for each household coming from bond holding costs.

Equilibrium definition

Given a time path of shocks $\{\{\eta_{t-1}^k,\, \epsilon_{it}^k,\, \{\varepsilon_{jt}^k\}_{j=i,u}\}_{k=L,S}\}_{t=0}^{\infty}$ and the initial position of households $\{k_{j0}, b_{j0}\}_{j=i,u}$, a competitive equilibrium for this economy is a sequence of prices $\{q_t, q_t^f, r_t^k, w_t\}_{t=0}^{\infty}$, private signals $\{\{s_{jt}^k\}_{j=i,u,\,k=L,S}\}_{t=0}^{\infty}$, invididual policies for households $\{\{c_{jt}, l_{jt}, b_{jt}, k_{jt}\}_{j=i,u}\}_{t=0}^{\infty}$, policies for the final good producer $\{k_{t-1}, l_t\}_{t=0}^{\infty}$, and policies for the investment firm $\{x_t\}_{t=0}^{\infty}$ such that

1. $\{\{c_{jt}, l_{jt}, b_{jt}, k_{jt}\}_{j=i,u}\}_{t=0}^{\infty}$ maximize (23) subject to (27) for better and worse-informed households given the vector of prices, private signals, and the expectation disturbances.

2. $\{k_{t-1}, l_t\}_{t=0}^{\infty}$ solve the representative firms maximization problem (12) given the vector of prices.

3. $\{x_t\}_{t=0}^{\infty}$ is the investment goods sector's optimal policy, maximizing (14) given the vector of prices.

4. Markets clear

   (a) Labor market: $l_t = \lambda l_{it} + (1-\lambda) l_{ut}$

   (b) Stock market: $k_t = \lambda k_{it} + (1-\lambda) k_{ut}$

   (c) Bond market: $0 = \lambda b_{it} + (1-\lambda) b_{ut}$

   (d) Final good market: $y_t = c_t + x_t$

   (e) Aggregate consumption follows: $c_t = \lambda c_{it} + (1-\lambda) c_{ut}$

Model Solution

The model is not stationary due to the productivity process. For this reason, I work with a stationary transformation of the economy. The solution and details are presented in Appendix A.2. A key point in the model is the state vector. In particular, the state vector will be different depending on whether one deals with individual or aggregate variables. Individuals variables, such as individual consumption, labor supply, capital, and bond holdings, will depend on the particular agent's conditional expectation. Aggregate variables at the representative household level will depend on the average expectation of the agents that belong to the household. Prices and aggregate variables such as aggregate consumption, labor, and physical capital will depend on representative households' average conditional expectations. In Appendix A.2, I show that the model's equation can be expressed as follows

$$f_1\left(S_{jt}\right) = \mathcal{E}_{jt}\left[f_2\left(S_{jt}, S_{jt+1}\right)\right] \tag{29}$$

The individual state variables $S_{jt} = \{S_t, \mathcal{E}_{jt}[\eta_{t+1}^L], \mathcal{E}_{jt}[\eta_{t+1}^S]\}$ are a function of the commonly known state variables which are given by the beginning-of-period stock of capital k_{t-1}, the beginning of period stock of capital of the better-informed household k_{it-1}, the beginning-of-period stock of bonds of the better-informed household b_{it-1}, the level of long-run productivity process ω_{t-1}, the current period value of short and long-run shocks η_t^L and η_t^S, and the average expectations. I collect this variables into the following vector $S_t = \{k_{t-1}, k_{it-1}, b_{it-1}, \omega_{t-1}, \eta_t^L, \eta_t^S, \{\bar{\mathbb{E}}_t^L\}_{jt}, \{\bar{\mathbb{E}}_{jt}^S\}_j\}$. Besides, the long and short-run next period shocks' conditional expectations are part of the individual state vector. Aggregate expectations for each of the productivity shocks are given by

$$\overline{\mathbb{E}}_{jt}^{k} = \int \mathcal{E}_{jt}\left[\eta_{t+1}^{k}\right] dj = \int \mathbb{E}_{jt}\left[\eta_{t+1}^{k}\right] dj + \varepsilon_{t}^{k} \qquad \text{for } k = \{S, L\} \tag{30}$$

where in the second equality, I use the definition of near-rational expectations in equation (22). The following proposition shows how the model is solved. It also states how the individual-level variables and the aggregate variables and prices are affected by the economy's information structure.

Proposition 1 (Recursive Equilibrium) *Given the equilibrium definition above and the model structure in the system of equations* (30)*, the model recursive equilibrium is characterized by the following conditions:*

1. *Agents' optimal policies depend on the individual state of the economy S_{jt}. Then, any individual variable can be expressed as*

$$f_{jt} = f\left(S_t, \mathcal{E}_{jt}\left[\eta_{t+1}^{L}\right], \mathcal{E}_{jt}\left[\eta_{t+1}^{S}\right]\right) \tag{31}$$

2. *Aggregate variables and prices depend on the economy's current state and the average expectations but not on households' individual conditional expectations. Then*

$$f_t = f\left(S_t\right) \tag{32}$$

The proof of the result is in the Appendix A.2. Another important point here is the fact that I implicitly assume that households observe $\overline{\mathbb{E}}_{jt}^{k}$ for $k = \{S, L\}$. For this, I need a condition that states a public signal that arises as an invertible function of some price or aggregate variable in the economy. In this dynamic setting, it is impossible to obtain a closed-form solution of this mapping, so I verify this quantitatively. Since, in this case, the model variables depend on four average expectations, I need four different sources of public information such that households can infer these average expectations. The following condition states this

Assumption 2 *The price of capital q, the price of bonds q^f, the wage rate w, and the return on capital r^k are invertible in $\{\overline{\mathbb{E}}_{jt}^{L}\}$ and $\{\overline{\mathbb{E}}_{jt}^{S}\}$, conditional on knowing all other state variables in the economy.*

I verify this result numerically. Given this condition, households can learn about $\{\overline{\mathbb{E}}_{jt}^{k}\}$ by observing these prices. Hassan and Mertens (2017) suggested that there are more combinations of variables that can inform households about average expectations. However, to stay close to their solution technique, I assume that households learn about average expectations from the model's asset prices.

3.3 Calibration

In this section, I parametrize the model to match certain moments in the data. The model is calibrated at the monthly frequency. I start by setting a subset of parameters following the literature in long-run risk models. Then, I calibrate the remaining parameters to be consistent with some macro and micro moments described bellow. For the macro moment, I focus on time series statistics matching the dynamics of US variables over the period 1947 - 2015.

Externally set parameters: The subset of parameters externally set are summarized in Table 5. In the case of the household sector, I set the intertemporal elasticity of substitution (IES) ψ to 2.0. Bansal and Yaron (2004) explain that an IES greater than one is key to obtain an average risk-free rate and its standard deviation at a low level. In addition, it is key for the first moment of excess returns to be positive, as in the data. The macroeconomic literature tends to use IES lower than one[12]. However, unlike my model, this parameter in these studies controls both the IES and the complementarity between consumption and labor. In my model, the parameter that controls this complementarity is χ, which is set to 0.2 following Croce (2014). The parameter λ is the measure of better-informed households in the model. Since it is difficult to find a direct measure of this parameter in the data, I use the measure of agents regarded as better-informed in the empirical section of this paper. Recall that I define that measure as the agents that belong to the top 20% of the distribution and who show an active trading behavior. More than half of the agents at the top of the distribution show an active trading behavior. For this reason, in the model, I set λ to 0.12.

On the production side, the capital share α on the final good sector is set to 0.34, which is a standard value in the literature. I set the persistence parameter and the volatility of the long-run component to be small but persistent. In particular, I set the persistence parameter ρ to be 0.8 in annual terms and the volatility parameter to be around 1.1% that of the short-run component following Hassan and Mertens (2017). For the investment sector, the parameters ν_0 and ν_1 depend on calibrated parameters. These are set so that the capital adjustment cost and its first derivative are zero in the steady-state.

For the information parameters, I use the estimates in Hassan and Mertens (2017). This paper presents a representative agent economy with dispersed information. I use their estimates for the common error process of equation (22) and for the aggregate noise in private signals that I discuss below. Then, since these authors use the Survey of Professional Forecasters (SPF) to estimate the

[12] See, for instance, Barsky, Juster, Kimball, and Shapiro (1997), Hall (2009), and Kekre and Lenel (2020)

precision of the private signal, I use these estimates for the private signal process of the better-informed agent. Then, I will calibrate the processes for the worse-informed agent to match two moments in the survey data discussed below.

Calibrated parameters: I calibrate the remaining model parameters to target some macro moments that are standard in the literature. I aim to reproduce some business cycle moments, asset price moments, and portfolio composition presented in the empirical section of the paper. I use the simulated method of moments (SMM) to calibrate the parameters in Table 6. In particular, I simulate the economy 100 times for 840 periods (that is 70 years using a monthly calibration) with a burning sample of 200 periods to reduce the effect of initial conditions. I target six moments computed using annual data for the period 1948-2015 for the business cycle moments. The first moment is the average real risk-free rate calculated using the annual 3-month T-bill minus the CPI inflation. The second moment is the average excess return which is obtained from Kenneth French webpage. The third moment is the annual average investment-output ratio. The fourth moment is the annual average per-capita output growth. The fifth moment is the annual average short-run standard deviation. Note that I use the short-run volatility to match this moment and calibrate the long-run standard deviation such that the ratio between these two is 0.11. The last business cycle moment is the ratio of investment to output volatility. The Appendix B presents all the data sources and how these moments are computed. Note that both production sectors in my economy do not hold levered positions. However, in the data, firms use debt to finance their investment projects. For this reason, I follow Croce (2014) and define the levered excess return $r^{Lev}_{ex,t}$ as follows

$$r^{Lev}_{ex,t} = \phi^{lev}\left(R_t - R^f_{t-1}\right) + \varepsilon^{ex}_t$$

where ϕ^{lev} is set to 2.0 and $\varepsilon^{ex}_t \sim N(0, \sigma^{ex})$. The parameter ϕ^{lev} is consistent with estimates in Rauh and Sufi (2012). The shock ε^{ex}_t is a cash-flow shock, and it is necessary to increase the volatility of the excess return. This shock does not affect the level of excess return. The standard deviation of this is set to 6.5% in annual terms, as in Croce (2014). The private information precision for the long and short-run productivity processes of the worse-informed agent is calibrated so that the average forecast error in the model matches that observed in the SPF and the ratio between the forecast error between the better-informed and the worse-informed households matches that of the 12 percentile with respect to that of the 88 percentile in the same survey. I use this ratio since the measure of informed agents in the model is $\lambda = 0.12$. In the Appendix B, I explain how these forecast errors are constructed using the file for forecasts of individual participants. Finally, I want the model to match two moments of the cross-section distribution between better-informed and worse-informed households. These two moments are computed for the deterministic steady-state.

I use the PSID to calculate the ratio of Net Financial Wealth between both households[13]. The value of this ratio is 1.44. The second moment I target is the share of stocks for the worse-informed household[14]. In the data, the value for this variable is 0.33.

Table 6 compares the moments in the data to those computed using the model. As the table shows, the model does a fair job of replicating the business cycle moments. In particular, the model can replicate the levered excess return with a value of risk aversion that is not too high. This value is similar to that in Mehra and Prescott (1985) and Bansal and Yaron (2004). It is essential to mention that the fact that the model is calibrated at a monthly frequency helps to obtain a high equity premium without having a large risk aversion. This observation is highlighted in Bansal, Kiku, and Yaron (2007) where the authors explain that the market price of risk associated with long-run shocks have a negative relation with the decision horizon; hence, a lower frequency of the calibration will imply a lower excess return. The model is also able to replicate a low value for the risk-free rate. For the macro business cycle moments, the model does a good job in matching the volatility of output growth and the ratio between the volatility of investment to that of the output growth. The model produces a higher value for the average investment-output ratio. To reduce this value, one will need to target a lower excess return since RBC models feature a negative relation between the investment-output ratio and the capital return. Since I want to study the financial implications of economic shocks in the model and study their effects over heterogeneous returns, I will make the model better target excess returns.

Untargeted moments: Table 7 presents the value of some untargeted moments and the empirical counterparts obtained using the data discussed in Appendix B. In terms of asset pricing moments, the standard deviation of the risk-free rate is lower in the model than in the data. This is a standard problem of models with long-run risk which remains even with a broad set of values for IES and relative risk aversion, see, for instance, Table II of Bansal and Yaron (2004) and Table 3 in Croce (2014). The model also performs well in matching the volatility of consumption. In the data, personal consumption's annual standard deviation is 3.9%. In the model, aggregate consumption, which is equal to the weighted sum of the consumption for the better and worse-informed households, has an annualized standard deviation of 3.8%.

The model does a fair job of replicating the first-order autocorrelation of the real risk-free rate. In the data, it is 0.57, and in the model, this value is 0.55. Note that the autocorrelation of the levered

[13] In the model, this ratio is given by $\frac{\lambda(q_{ss}k_{iss}+b_{iss})}{(1-\lambda)\left(q_{ss}k_{jss}+b_{jss}\right)}$. In the data, to construct the average net financial wealth for each group, I sum the holdings on stocks, bonds, checking and saving accounts, and private business minus the total debt (excluding mortgage debt)

[14] In the model this ratio is given by $\frac{(1-\lambda)q_{ss}k_{jss}}{q_{ss}k_{ss}}$.

excess return is -0.01 in the data and 0.0 in the model. The model presents a higher autocorrelation for consumption growth. In the data, this moment is equal to 0.5, and in the model it is 0.7. In terms of the correlation between consumption growth and investment growth, the model generates a value of 0.46, which is close to the data. Finally, the correlation between consumption growth and the excess return in the model is 0.08, which is a bit higher with respect to the data's value, 0.05.

4. Results

In this section, I analyze the effect of information frictions in the transmission of the shocks to the economy. I start by highlighting the role of differences in information by presenting impulse response functions (IRF) for the economy described above with respect to an economy in which agents do not incur in expectation errors; that is, the variance of ε^k in (22) is equal to zero. Then, I study the effects of uncertainty in the model and compare the results of a model-based uncertainty measure with those obtained in the empirical section.

The effect of near-rationality: In this section, I explain the extent of the near-rationality assumption in the model's results. Recall that agents in the model form expectations using the following formula

$$\mathcal{E}_{jt}\left[\eta^k_{t+1}\right] = \mathbb{E}_{jt}\left[\eta^k_{t+1}\right] + \varepsilon^k_t$$

where $\mathbb{E}_{jt}\left[\eta^k_{t+1}\right] = \mathbb{E}\left[\eta^k_{t+1}|S_{jt}\right]$ is the conditional expectation of agent j about the next period shock η^k. In the Appendix A.2, equation (A.32) presents the functional form for the aggregate expectation for both types of representative households. As the equation shows, the average expectation is a function of next period productivity shock η^k_{t+1} and the near rational shock ε_t; that is

$$\overline{E}_{jt} = \pi^k_{j0} + \pi^k_{j1}\eta^k_{t+1} + \pi^k_{j2}\varepsilon^k_t$$

Agents in the model display a fully rational behavior when the variance of ε^k_t is zero. Therefore, the near-rational expectation coincides with the rational one. In this case, the loading coefficient of η^k_{t+1} in the average expectation equation is equal to one; that is, any future news about the productivity shock is fully observed at time t. In this case, the private signal is useless since all the information is provided by prices, which act as a public signal. When the economy features near-rationality; that is, the variance of ε^k_t is positive, the coefficient is a decreasing function of the private signal variance. Then, a better-informed household has an advantage with respect to the worse-informed one. Figure 8 presents the coefficient π^k_{j1} for $k = \{L, S\}$. The blue line corresponds to the loading coefficient for the fully-rational economy. In this scenario, differences in private information will not generate any difference for average expectations across households. The black line reports the loading coefficient for the near-rational economy. When this occurs, information disparities matter and affect the average expectation of each household. The red-dotted lines report the values of the coefficients for the better and worse-informed agents. As the figure suggests, the loading in the coefficient is higher for the better-informed household; hence, this household will adjust by more when there is any new information in the economy.

To further explain the role of near-rationality and the effect of information frictions across households, Table 8 presents the simulation results for a set of variables in the model. The first column reports the outcome of the benchmark economy; that is, the economy where households display a near-rational behavior and the differences in the precision of the private signal between households matter. The second column reports the outcome of the model when households behave fully rational. The first panel presents the information side in each economy. One thing to note is that the ratio of conditional to unconditional expectation is around 50% for the better-informed household. This means that the household with a private signal with higher precision can reduce the uncertainty about next period realization of each shock by half. For the worse-informed households, this ratio is higher as a result of a private signal with higher variance. In the case of the fully rational economy, these ratios are zero. This highlights the fact that private information is useless in the fully-rational economy.

The second panel of Table 8 presents some asset pricing moments. First, note that the risk-free rate is higher in the benchmark economy with respect to the fully rational one; the annualized interest rate is 0.79% and 1.25%, respectively. Near-rationality increases risk in the economy since it delays the resolution of uncertainty about future productivity shocks. Hence, households engage in precautionary savings to reduce their risk exposure. In addition, households require a higher equity premium. As the table shows, the average excess return is 4.9% for the benchmark economy and 3.9% for the fully-rational economy.

The third panel of Table 8 presents micro-moments that show how information differences impact financial outcomes between both types of households. First, I define individual return to net worth and share on risky assets as

$$
\begin{aligned}
r_{jt+1} &= \mathrm{sR}_{jt}\left(r^{e}_{t+1}\right) + r^{f}_{t} \\
\mathrm{sR}_{jt} &= \frac{q_t k_{jt}}{q_t k_{jt} + b_{jt}}
\end{aligned}
$$

Note that in the benchmark economy, the average difference in returns to net-worth across both types of households are 1.0% in annual terms. In the case of the fully rational economy, this difference decreases to 0.7%. According to portfolio theory, investors allocate a higher share of their wealth in stocks and lower share in fixed-income assets when they have information that future returns are higher (see, for instance, Brandt (2010) and Campbell and Viceira (2001)). This is indeed the case in the fully rational economy as households allocate a higher share of their wealth into capital. Then, even with a higher share in the risky assets, the return difference is lower in the fully rational economy, which highlights the role of information frictions among households in increasing return differences. Another result of the model is the persistence of return differences. As the table shows, the first-order autocorrelation of this variable is 0.3. This value suggests that better-informed household can sustain a higher return for more than one period. This is in contrast with the value under fully-rationality, which is -0.34. Figure 9 reports the histogram of average annualized returns for the 100 simulations (each simulation is run for 840 periods, which corresponds to 70 years). As the figure shows, the return difference is skewed to the left for fully rational economics, highlighting the fact that under this information structure, the benefits of having better precision in private signals are not important. Finally, the table shows that under the near-rational assumption when information differences among households matter, the wealth share of the better-informed household is 1.4% higher. This is in line with the empirical evidence suggesting that return heterogeneity is one of the mechanisms to explain wealth inequality.

Figures 10 and 11 present impulse response functions (IRF) for the real and the financial sector when the economy is hit by a two standard deviation shock to η^L. The figure compares the dynamics for the benchmark economy (black lines) and for the fully rational economy (blue lines). The shocks materialize in period 1 (see the dashed vertical lines); however, given the definition of average expectation above, households form expectations in period 0 when they receive the information about the future shock. The upper-left panel of Figure 10 presents the productiviy growth Δz_t given in (10). The upper-right panel shows the IRF for aggregate investment. The panel shows that the fully rational economy adjusts in period 0; that is, one period before the shock materializes. This comes from the fact that the loading coefficient π^k_{j1} on the average expectation is equal to one for the fully rational economy; hence, the households learn about the shock at period 0 and adjust their behavior immediately after the information arrives. For the benchmark economy, the loading coefficient is lower than one, and hence one observes a sluggish adjustment. Given that this loading coefficient is a decreasing function of the private signal variance, the worse-informed agent reaction is even slower. Also, because the worse-informed household's measure is 88%, its effect over the aggregate economy is higher. As a result, the economy adjusts by less in period 0 when the shock is not yet realized. The lower-left panel shows the same pattern for consumption, under the fully rational economy consumption adjust in period 0. In contrast, for the benchmark economy, it adjusts by more in period 1 when the shock materializes. To gain some intuition behind the difference between the adjustment of the better and worse-informed households, the lower-right panel shows consumption across households. The dotted-gray line shows consumption adjustment for the better-informed household. As the figure shows, consumption adjusts more in period 0 because this household receives a better private signal, which makes the loading coefficient in the average expectation to be higher. The response of the worse-informed household is more sluggish, and because this household has a higher measure, it will affect by more the response of aggregate consumption.

The response of aggregate consumption and aggregate investment after a long-run productivity shock is consistent with the literature on long-run risk models. Note that this shock is very persistent since it directly impacts ω_t (see equation 11). This generates strong responses on consumption and portfolio allocation. In addition, as suggested by Croce (2014), this shock generates a substitution and an income effect that operate in opposite directions. First, a positive long-run productivity shock generates a substitution effect that makes saving profitable and hence increases investment and reduces aggregate consumption. Second, there is an income effect since the household feels richer because of the higher capital price; this makes each household to increase consumption. When the IES is above one, the substitution effect dominates, and hence households reduce consumption to increase savings. Figure 10 shows this pattern since after a positive long-run productivity shock, investment growth increases and aggregate consumption growth decreases.

For the financial side of the economy, Figure 11 presents IRFs for the benchmark and the fully rational economy. In both economies, investment increases after a positive long-run shock. This generates an increase in the price of capital, as shown in the upper-right panel of the figure. Moreover, the higher capital price translates into a higher capital return. In addition, this shock increases the risk-free rate as well; however, the increase in the capital return outperforms that of the risk-free rate, which makes the excess return to increase after the shock. The model also predicts a slower adjustment for the financial variables in the model under the benchmark economy with the same forces explained above driving the results.

Figure 12 presents the IRFs for some cross-sectional variables. The upper-left panel presents the share in the risky asset of the better-informed household. After a positive long-run productivity shock, the price of capital starts to increase. Since this household has better news of the future productivity shock, it starts decreasing the share on the risky asset suggesting a timing-the-market strategy. This is in line with the empirical evidence I presented above, however in opposite direction because here the shock is good news, which suggests that when a bad economic shock materializes and the price of capital drops, the better-informed investor reacts by increasing the share on the risky asset and decreasing it thereafter. The opposite occurs in the case of the worse-informed agent. This result also highlights the advantage that the better-informed household has due to the higher precision of her private signal. The bottom-left panel presents the return to net worth difference. As the panel shows, the difference persists for around four periods, which aligns with the autocorrelation that the model produces in the simulations (see the first column of Table 8). Finally, the bottom-right panel presents the evolution of wealth shares. Note that the better-informed household (black line) benefits more from the shock. The wealth share for this household increases, and then it slowly reverts to the initial level. This is also in line with the simulation results, which suggest that wealth share for the informed household is higher when information frictions are relevant.

The above IRF analysis pertains to the long-run productivity shocks. Figures 13 - 15 present the results for a short-run productivity shock. There are important differences between these two. First, short-run productivity shocks induce a perfect correlation between consumption and investment growth (different from the case of long-run shocks in which they move in opposite directions), so in this case, the effects of the substitution effect are dampened by the income effect because the shock is short-lasting, and the future gains of higher savings are not as profitable. One way to see this is the upper-right panel of Figure 14 which shows that the increase of the capital price is not as persistent as with the long-run shock. As a result, aggregate consumption growth is positive in this case. Second, the benchmark and the fully rational economy behave similarly in this case. The reason is that the advantage of information is not as valuable because of the shock's transitory nature.

Endogenous uncertainty and returns' dynamic In this section, I show that the model can explain the dynamic facts presented in the empirical section. For this purpose, I build additional definitions that allow me to establish a measure of uncertainty in the model. This concept, as I explain below, will follow the empirical approach presented in Ludvigson, Ma, and Ng (forthcoming). Hence, uncertainty will be an endogenous object in the model. Then, I perform the type of regressions I conducted in the empirical section and show that the model can qualitatively replicate the observed results in the data.

To highlight the role of uncertainty, I include an aggregate noise component into the private signal of the agents within each household. This extra random variable increases the variance of the signal and hence reduces the precision of the information received ex-ante. Using the expression in equation (20), the private signal for each type of agents becomes

$$s_{jt}^L = \eta_{t+1}^L + e_t^L + \sigma_j^L \, \epsilon_{jt}^L$$
$$s_{jt}^S = \eta_{t+1}^S + e_t^S + \sigma_j^S \, \epsilon_{jt}^S$$

where $e_t^k \sim N(0, \sigma_{ke}^2)$ for $k = \{L, S\}$ is an aggregate shock common across agents. Once I include this new shock, variables in the model are affected by three exogenous sources of variation: the short-run productivity component, the long-run productivity shock, and the aggregate noise in private signals. The last column of Table 8 presents the results of the model simulation when I include the aggregate noise component in the private signals. As the results show, aggregate noise does not significantly change many of the model's implied moments compared to the benchmark simulation in the first column. Something to note is that the levered excess return is higher, and the risk-free rate is lower because of the model's additional risk. Also, the ratio of forecast errors increases from 38% to 57%, suggesting that the better-informed household is more impacted by the additional noise in the private signal. In the model, the $h-$step ahead forecast errors of output growth for a household of type j are

$$\text{Ferr}_{jt}^h = (dy_{t+h} - E[dy_{t+h}|S_{jt}])^2$$

where $dy_{t+1} = \ln y_{t-1} + \ln y_t + \Delta z_t$ is the output growth. To gain some intuition on the effects of information assumptions, Figure 16 presents the one-step ahead forecast errors for output growth. The upper-right panel shows the results for the benchmark economy. The gray bars report the forecast errors for the better-informed agent, the red ones are forecasts errors for the worse-informed agent, and the blue bars are the average forecast errors, which I calculate by equally averaging across households, that is, $\text{Ferr}_t^h = 0.5\text{Ferr}_{it}^h + (1 - 0.5)\text{Ferr}_{ut}^h$. Two things are worth mentioning about this panel; first, there is disagreement about output growth across agents. This dissent comes from the difference in the precision in private signals. Hence, forecast errors are higher for the worse-informed household. Second, the fact that the measure of worse-informed agents is higher makes the cross-sectional average forecast errors to be higher. Note that the blue bars are skewed to the right. The upper-right panel shows the forecast errors for the fully rational economy. Note that in this case, and given that households know the realization of the shock ex-ante, the forecast errors are the same across households and a factor of 10^{-6}. Hence, under the rational economy, households do not make forecast errors, and there is not any room for disagreement about their forecasts. The lower-left panel presents the results for the economy with aggregate noise in the private signal. Note that in this case, the household for whom forecast errors increase by more is the better-informed household. The reason is that the loading coefficient on average expectation is a decreasing function of the variance of the private signal. By including an additional noise term in the signal structure, one is effectively reducing the precision of the signal. Finally, the lower-right panel shows the cross-sectional average forecast errors for the benchmark economy (blue) and the economy with aggregate noise in the private signal (brown). Note that the latter is a little more skewed to the right; however, the difference is small, and this is because under my definition of cross-section average forecast errors, the worse-informed household has a higher weight and, as I explained before, this agent is not as affected by the increase in noise since his private signal was a priori not as informative.

The foregoing analysis of forecast errors helps advance the definition of uncertainty in the model. Following the lead of Bloom (2009), a growing literature argues that uncertainty shocks, along with certain type of frictions, are driving forces of business cycles in general equilibrium[15]. In this case, the causality goes from uncertainty to economic outcomes. In my model, I do not consider stochastic volatility (all my three shocks have constant variances); then, I follow the literature that suggests that uncertainty is an outcome, rather than the cause, of business cycles[16].

In the empirical section of the paper, I use a measure of financial uncertainty based on Ludvigson, Ma, and Ng (forthcoming). In defining uncertainty, this paper follows Jurado, Ludvigson, and Ng (2015) which asserts that uncertainty is defined as the conditional volatility of a disturbance which is not forecastable from the perspective of agents in the economy. This study defines $h-$period ahead uncertainty in the variable $f_{kt} \in F_t = (f_{1t}, \cdots, f_{Nt})'$, denoted by $\mathcal{U}^f_{kt}(h)$, to be the conditional volatility of the forecast errors of future values of this variable. Formally,

$$\mathcal{U}^f_{kt}(h) \equiv \sqrt{\mathbb{E}\left[\left(f_{kt+h} - \mathbb{E}\left[f_{kt+h}|I_t\right]\right)^2|I_t\right]} \tag{34}$$

where I_t is the information set available at period t. An index of uncertainty is constructed by summing individual uncertainty at each period as follows

$$\mathcal{U}^f_t(h) \equiv \frac{1}{N}\sum_{k=1}^{N}\mathcal{U}^f_{kt}(h) \tag{35}$$

My definition of uncertainty will be a little different since the framework in Jurado, Ludvigson, and Ng (2015) requires time-varying volatility to compute the conditional expectations in the formulas above. My definition will be based on the cross-sectional dispersion of households' subjective expectations. Recall that in my model, the relevant expectation for each type of household is $\mathcal{E}\left[.|S_t\right]$ which is the sum of the rational conditional expectation and the disturbance ε (see equation 22). Hence, my measure of uncertainty is

$$\mathcal{D}^{Af}_{kt}(h) \equiv \sqrt{\sum_{a=1}^{A}\frac{1}{A}\left(f_{kt+h} - \mathcal{E}\left[f_{kt+h}|S_{at}\right]\right)^2} \tag{36}$$

[15]Examples include Arellano, Bai, and Kehoe (2011), Bachmann and Bayer (2011), Schaal (2012), and, Christiano, Motto, and Rostagno (2014), among others.

[16]Examples of theoretical models in which uncertainty is obtained endogenously are Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini (2011), Decker, D'Erasmo, and Moscoso Boedo (2016), and Benhabib, Liu, and Wang (2016).

where A denotes the number of households and k the relevant variable. Finally, I follow Jurado, Ludvigson, and Ng (2015) by defining aggregate uncertainty as

$$\mathcal{D}_t^{Af}(h) \equiv \frac{1}{N} \sum_{k=1}^{N} \mathcal{D}_{kt}^{Af}(h) \tag{37}$$

In the empirical section of this paper, I focus on financial uncertainty. For this reason, I will consider just the price of capita when constructing the measure of uncertainty in (37). Figure 17 presents the measure of financial uncertainty along with the long-run productivity process ω_t in equation 11 and the productivity growth in 10. These variables are obtained by averaging, in each period, the realizations for each of the 100 economies. An important result of this exercise is that the correlation between financial uncertainty and long-run productivity process is -0.5, and the correlation of uncertainty with productivity growth is -0.2. This is important since the literature of uncertainty and business cycles stress that periods of low or negative growth are associated with higher uncertainty. Another important observation is that this correlation is higher when considering the long-run process due to the high persistence that this component presents.

With a measure of financial uncertainty in hand, I follow Ludvigson, Ma, and Ng (forthcoming), which constructs a measure of unanticipated uncertainty shocks. To do so, these authors estimate a three-variable structural vector autoregression (SVAR) with a measure of economic activity, an index of macroeconomic uncertainty, and an index of financial uncertainty. Then, using they propose an identification strategy that allows for simultaneous feedback between uncertainty and real activity. They refer to this approach as shock-based restrictions.

In my model, I implicitly assume that the aggregate noise shock in private signals causes households to incur in higher forecast errors and hence to increase the measure of uncertainty in the model. To isolate the effect of this shock on the non-linear response of the economy, I orthogonalize my measure of uncertainty with respect to the other two shocks in the model: (i) the long-run productivity shock η^L and the long-run component of of productivity growth ω and (ii) the short-run productivity shock η^S. Hence, I estimate the following regression

$$\mathcal{D}_{qt}^{2f}(1) = \beta_0 + \beta_1 \omega_t + \beta_2 \eta_t^L + \beta_3 \eta_t^S + \beta_4 \mathcal{D}_{qt-1}^{2f}(1) + \epsilon_t^D$$

hence the measure of unanticipated financial uncertainty shocks that I will use is $\{\widehat{\epsilon}_t^D\}$. With this variable, I run a panel data regression similar to the one in the empirical section. Then, I use Jordà (2005) local projection method to study the dynamic impact of the model financial uncertainty shock $\{\widehat{\epsilon}_t^D\}$ over return heterogeneity and portfolio allocation

$$f_{jt+h} = \alpha_h + \beta_h I_{jt} + \gamma_h \left(e_t^F \# I_{jt} \right) + \varepsilon_{t+h}$$

where f_{jt+h} denotes either returns to net worth or portfolio share on risky assets, I_{jt} is a categorical variable that takes value one for the better-informed household. I can do this in the model since I know with certainty the type of the representative households. The right-hand panels of Figure 18 present the estimate of γ_h for $h > 1$ using the simulated data. The left-hand side panels reproduce the dynamic results presented in the empirical section of the model. Note that the model does a fair job in explaining the effect of uncertainty shocks on returns to net worth across households. Moreover, the model qualitatively produce a decreasing portfolio share on risky asset; however, it cannot match the quantitative magnitude found in the data.

5. Conclusion

In this paper, I propose a theory that links heterogeneity in returns to information frictions among investors. Using a panel of American individuals, I present suggestive evidence that the returns to net worth are heterogeneous and positively correlated with wealth. Then, I establish new dynamic empirical facts that propose wealthier individuals assumed to have information advantages earn higher returns after an unexpected financial uncertainty shock hits the economy. To understand a potential mechanism behind these facts, I build a heterogeneous-agent model that highlights information frictions' role in explaining return heterogeneity and the heterogeneous effects of endogenous uncertainty on investors' performance.

Using the PSID, I show that the average cross-sectional performance decreases in recessions and document significant heterogeneity across returns when an adverse economic shock hits the economy. I also present evidence that returns to net worth are positively correlated with wealth. This positive correlation remains when I adjust the returns by the risk that investors face; that is, individual Sharpe ratio is positively correlated with wealth. Then, I establish new empirical facts in a dynamic setting. I estimate a linear panel data model for individual returns to net worth and show that individuals who trade with more intensity and belong to the top 20% of the distribution earn, on average, higher returns. I argue that the trading activity variable is a proxy for information advantage for individuals in the top 20%. I then study how trading behavior and the wealth distribution position affect portfolio performance when an adverse shock hits the economy. I show that after an unexpected uncertainty shock, individuals that actively trade and belong to the top 20% perform better than individuals that do not change their portfolio and do not belong to the top 20% of the distribution. I also present evidence that this seems to result from a reallocation of the portfolio after the shock, which suggests a timing-the-market strategy.

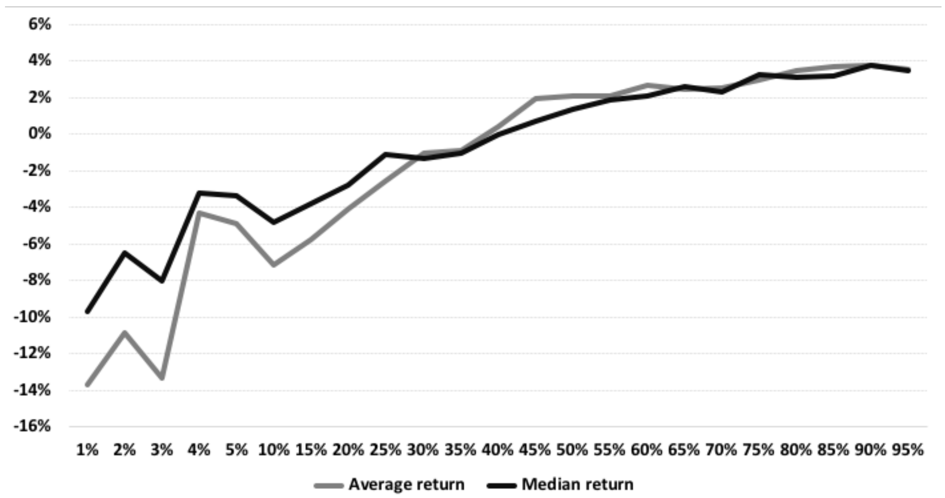
To interpret these facts, I propose a heterogeneous-agents model with informational frictions. In the model, two types of households coexist. Both receive private signals about the fundamental shocks in the economy; however, the signals' precision differs between them. The model does a fair job matching macroeconomic and financial moments in the data. The model also matches some cross-sectional moments of portfolio holdings and the dispersion of forecast errors from the Survey of Professional Forecasters.

Using the model, I study the importance of informational frictions on the heterogeneity of returns. The model predicts a higher difference in returns to net worth and a higher cross-sectional dispersion between the better and worse-informed agents. Then, and to relate the results with the empirical dynamic facts, I construct an endogenous measure of uncertainty following Ludvigson, Ma, and Ng (forthcoming). I show that after an unexpected financial uncertainty shock, the better-informed household can sustain higher returns for around four periods. Besides, the model predicts that this household will adjust the composition of the portfolio by increasing the share in the risky asset when the price has decreased and then decreasing this share as the price recovers.

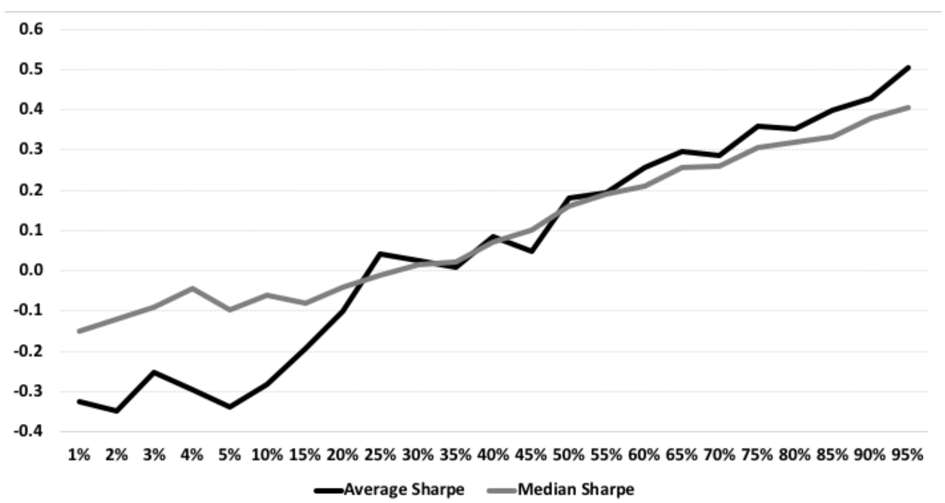
Figures and Tables

6. Figures

Figure 1: **Returns to net worth and Sharpe ratios across the wealth distribution**



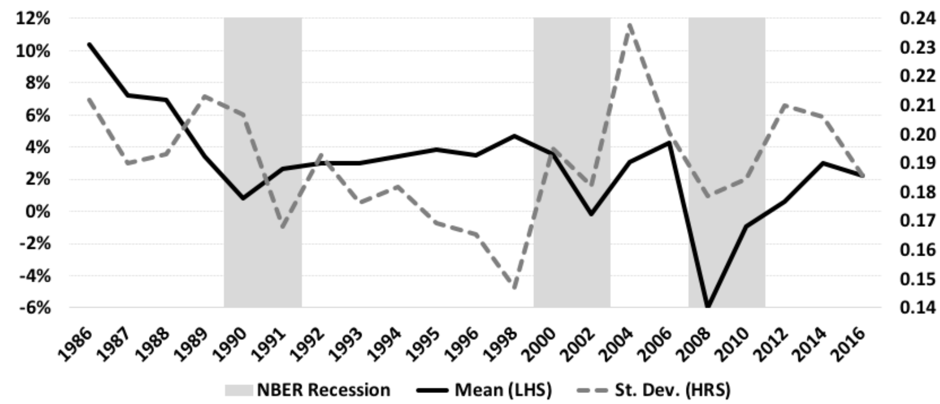
(a) Cross-sectional average and median return to net worth



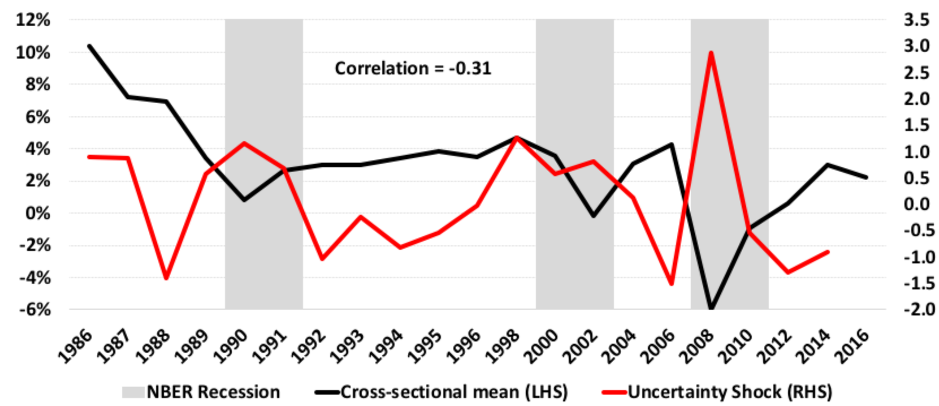
(b) Cross-sectional average and median Sharpe ratios

Notes: The upper panel presents returns to net worth across the wealth distribution. The gray line shows the cross-sectional average return for the pooled sample and the black line the cross-sectional the median return. The lower panel presents the Sharpe ratio calculated as $SR_i = \frac{\sum_{t_i=1}^{N_i}\left(r_{it}^{nw} - \bar{r}_i^{f}\right)}{\sqrt{\sum_{t_i=1}^{N_i}\left(r_{it}^{nw} - \bar{r}_i^{nw}\right)^2}}$. The sample spans the period 1986 - 2017.

Figure 2: **Net worth returns, the business cycle, and uncertainty**



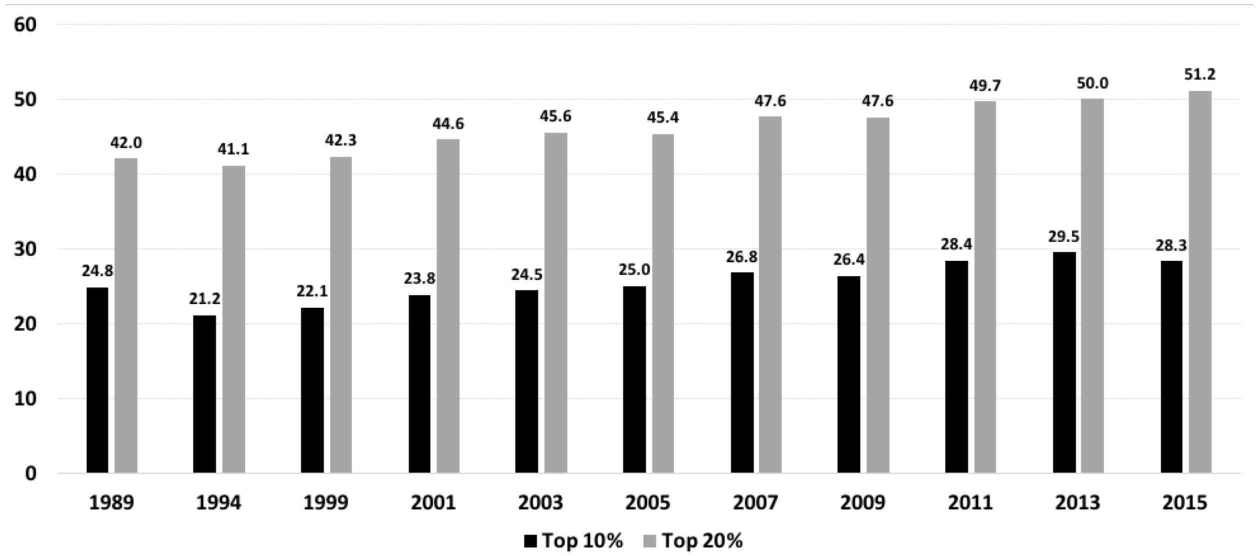
(a) Cross-sectional average return and cross-sectional returns' dispersion



(b) Cross-sectional average return and uncertainty

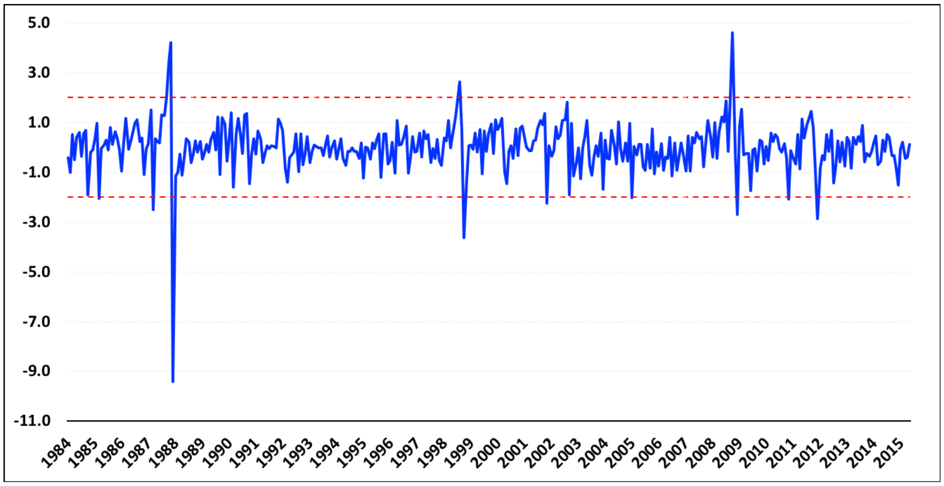
Notes: The upper panel presents the cross-sectional average return and cross-sectional returns' dispersion across time. Gray bars identify the NBER recession dates. The lower panel presents the cross-sectional average return and the measure of uncertainty used in the empirical section of the paper. The sample spans the period 1986 - 2017.

Figure 3: **Percentage of individual who adjust the portfolio**

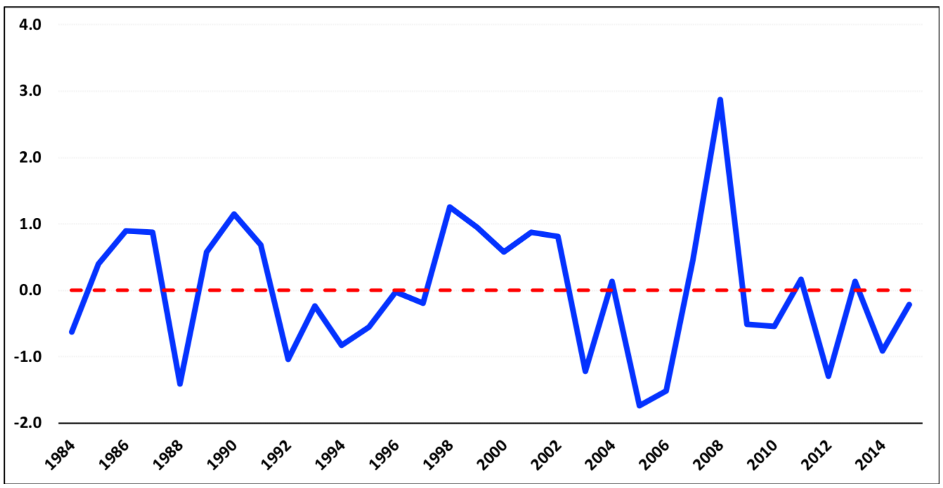


Notes: The figure presents the fraction of respondents who have adjusted their holdings of stocks in their portfolio since the last interview. The black bars are individuals in the top 10% of the wealth distribution and the gray bars are individuals in the top 20% of the wealth distribution. The sample spans the period 1989-2017.

Figure 4: **Financial uncertainty shocks**



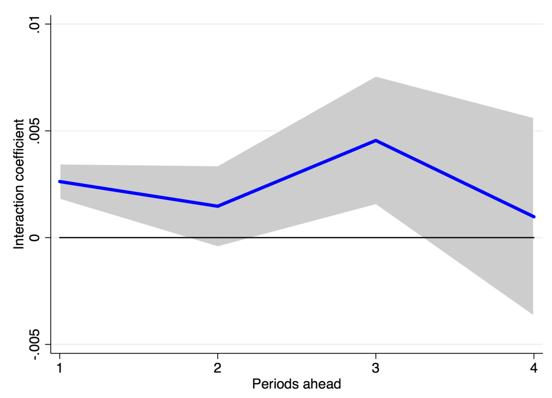
(a) Monthly uncertainty shock



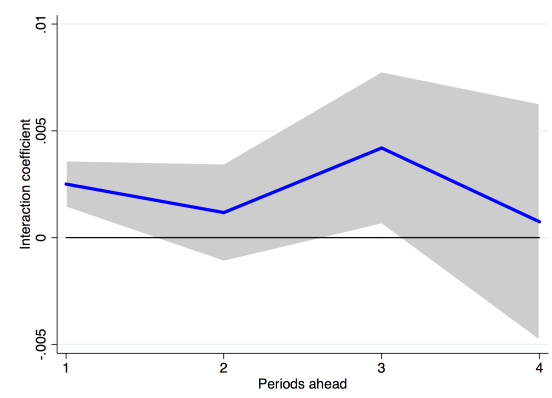
(b) Annual uncertainty shock

Notes: the figure shows results from the identified set VAR in Ludvigson, Ma, and Ng (forthcoming). The upper panel reports the time series of the structural shocks for one particular solution from this set, referred to in the text as the maxG solution. The lower panel shows the annual version of the shock. The sample spans the period 1984:01 to 2015:12.

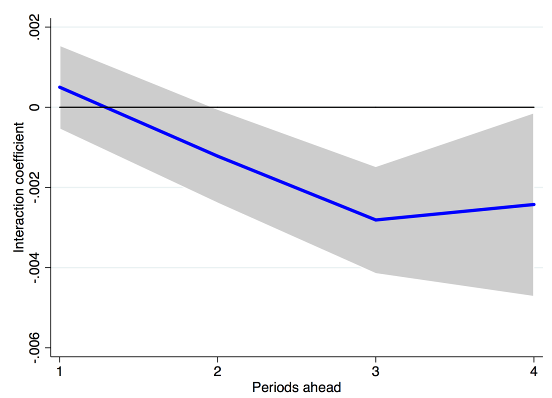
Figure 5: **Impulse-response functions after a financial uncertainty shock**



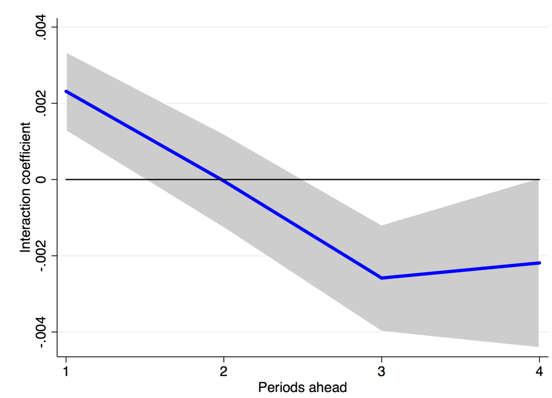
(a) Only includes active trading$_{it}$ in X'_{it}



(b) Includes the whole set of covariates in X'_{it}



(c) Only includes active trading$_{it}$ in X'_{it}



(d) Includes the whole set of covariates in X'_{it}

Notes: The figure presents the coefficient γ_h for the $h > 1$ projection regressions in (3) using Jordà (2005) local projection method. The upper panel presents the results for the return to net worth (r^{nw}_{it}). The lower panel presents the results for the share on stocks. Gray areas are the 90% confidence bands.

Figure 6: **Timing in the static model**

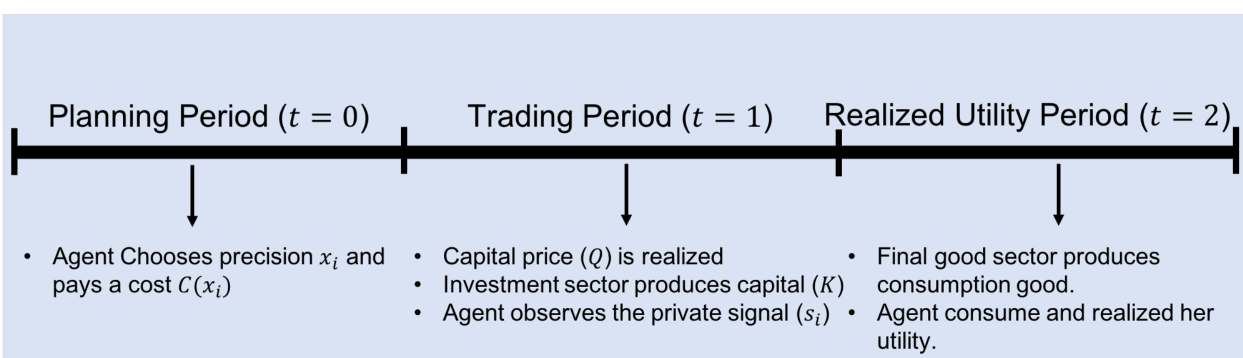
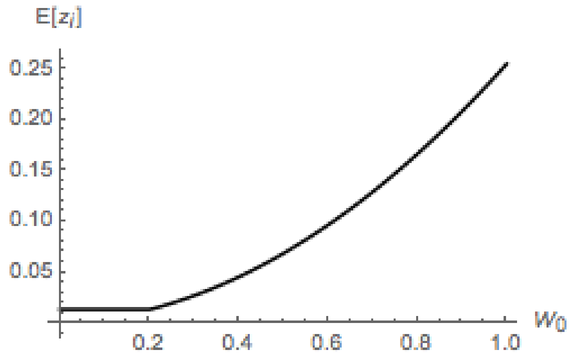
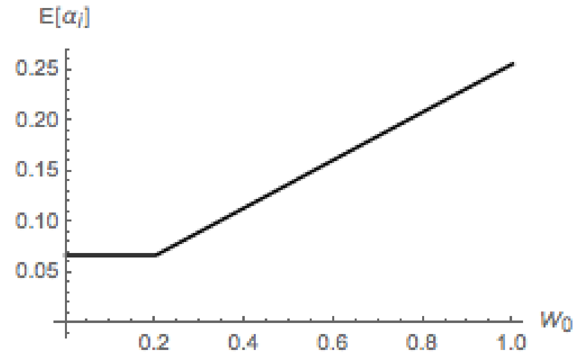


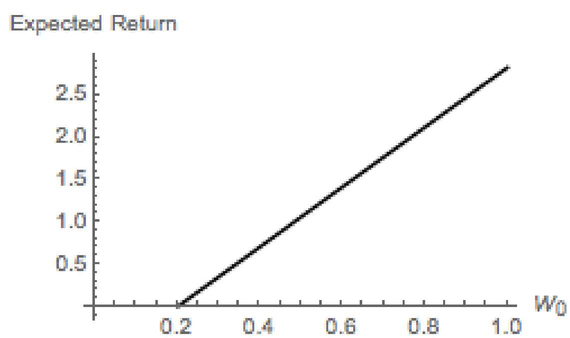
Figure 7: **Static model implications for returns**



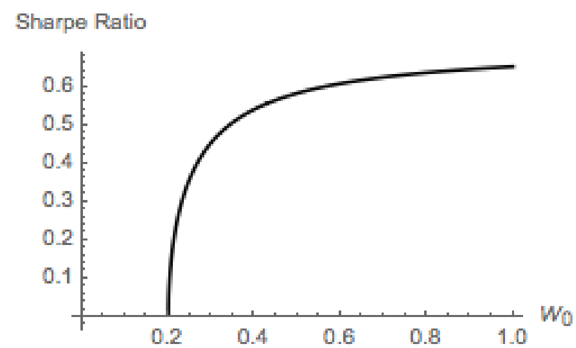
(a) Ex-ante holdings of capital in the portfolio



(b) Ex-ante share in the risky asset

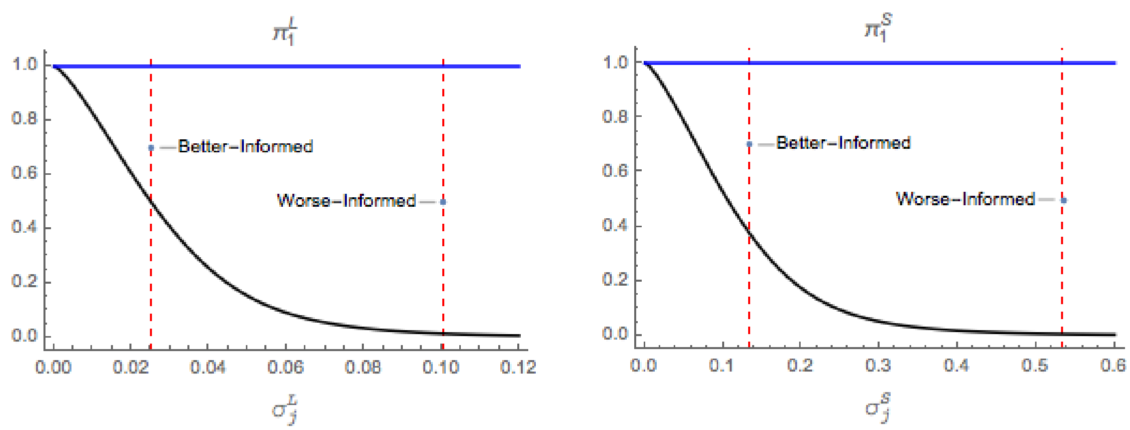


(c) Ex-ante returns to net worth



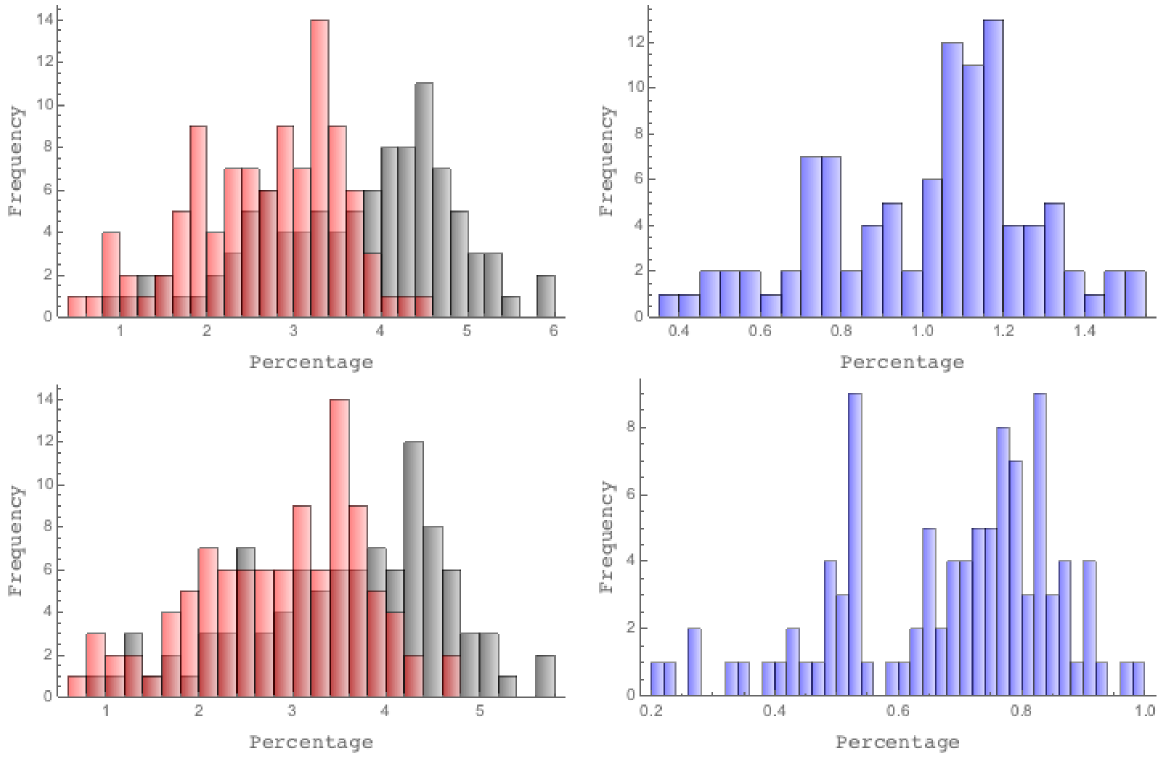
(c) Ex-ante Sharpe ratio

Figure 8: **Loadings for productivity shocks in average expectations**



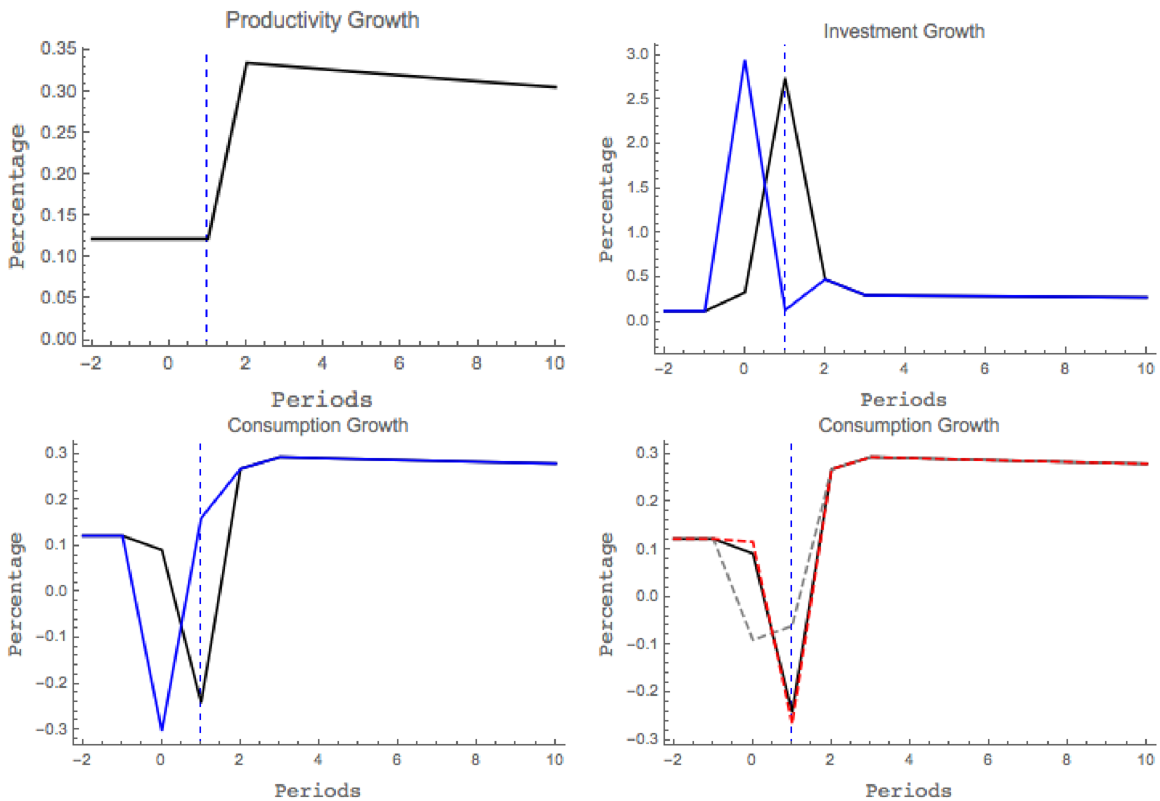
Notes: The figure reports the coefficient π_1^k for η_{t+1}^k in the average expectation. The left panel presents the coefficient for the long-run productivity shock and the right panel presents the coefficients for the short-run productivity shock. The black line is the function for the benchmark economy. The blue line reports the coefficient for the rational economy. The dotted-red lines report the coefficients for the better and worse-informed households for the benchmark calibration.

Figure 9: **Cross-section returns to net worth**



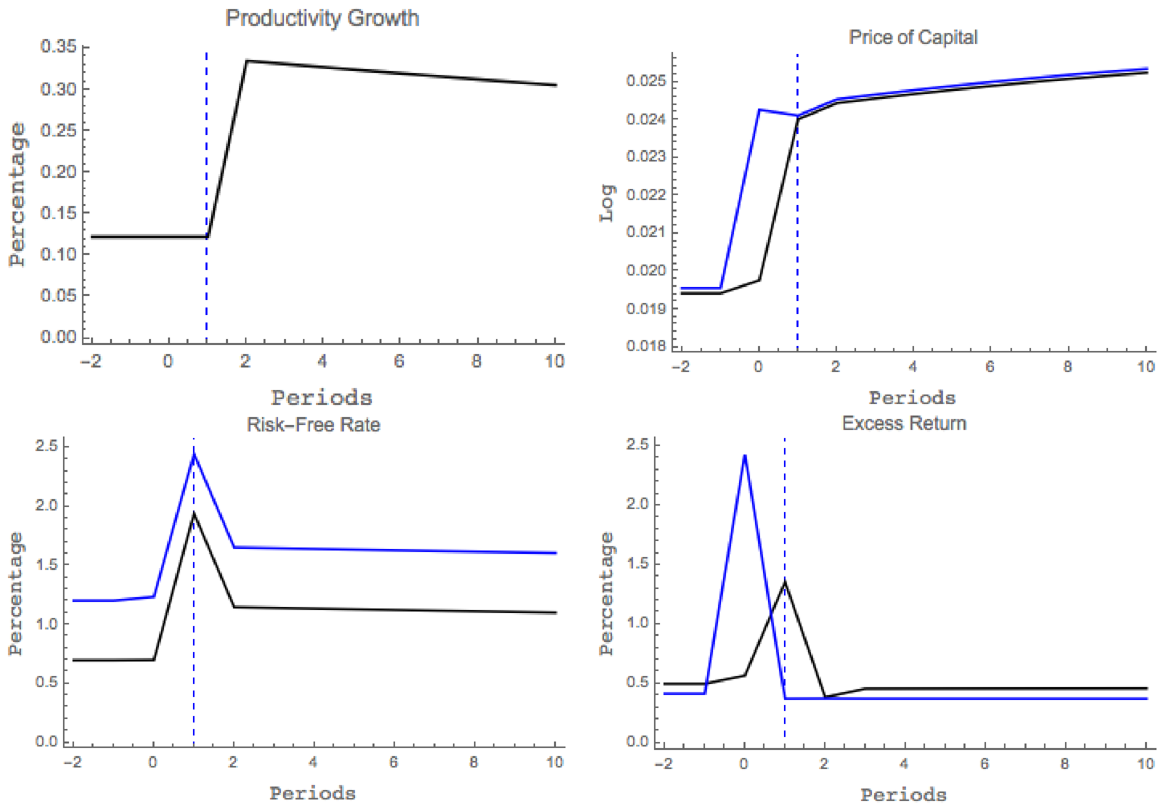
Notes: The figure reports the histogram of average annualized returns for the 100 simulations. The upper panel presents the results for the benchmark economy and the lower panel the results for the fully rational economy. The left panel presents the returns to net worth for the better-informed household in black and for the worse-informed household in red. The right panel presents the average annualized return difference.

Figure 10: **Impulse response functions for η^L: real sector**



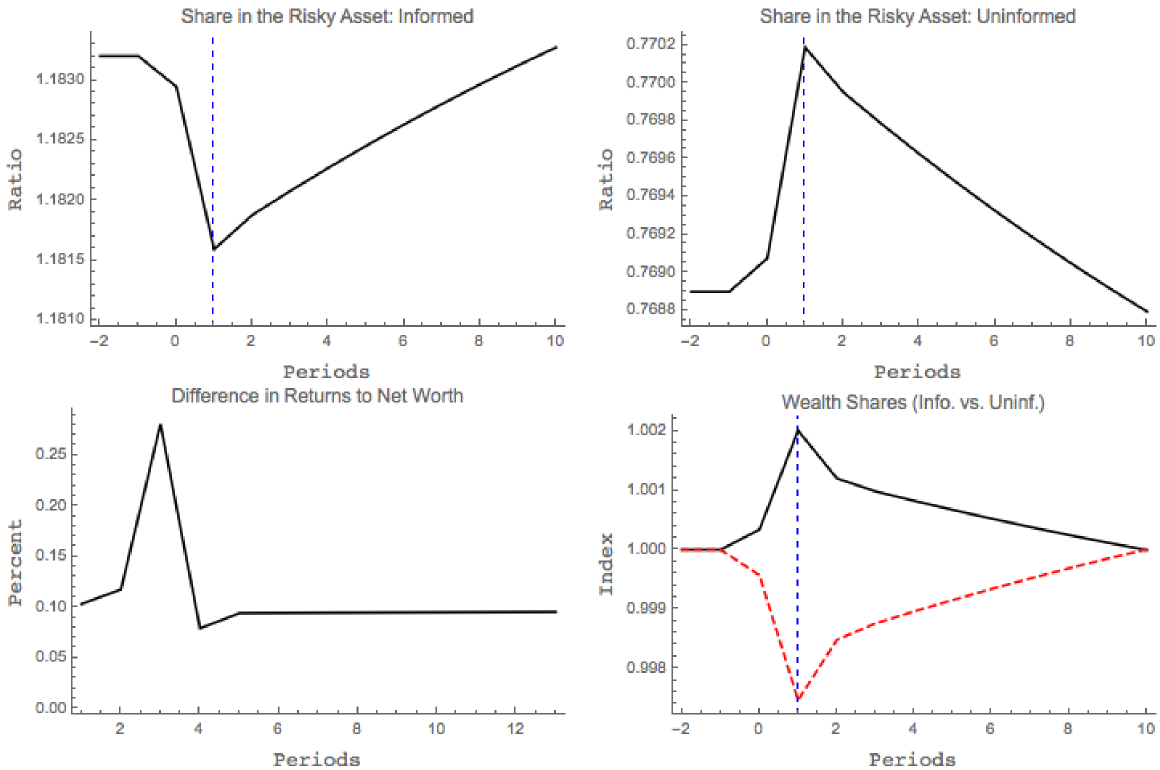
Notes: The figure presents the IRF for a 2 standard deviation shock on η^L that materializes in period 1. The upper-left panel presents the shock. The upper-right panel presents the investment growth rate. The lower-left panel shows the aggregate consumption growth rate and the lower-right panel presents consumption growth rate for each representative household. The black lines show the IRF for the benchmark economy and the blue ones for the fully rational economy. The dashed vertical lines show the time at which the shock is realized.

Figure 11: **Impulse response functions for η^L: financial sector**



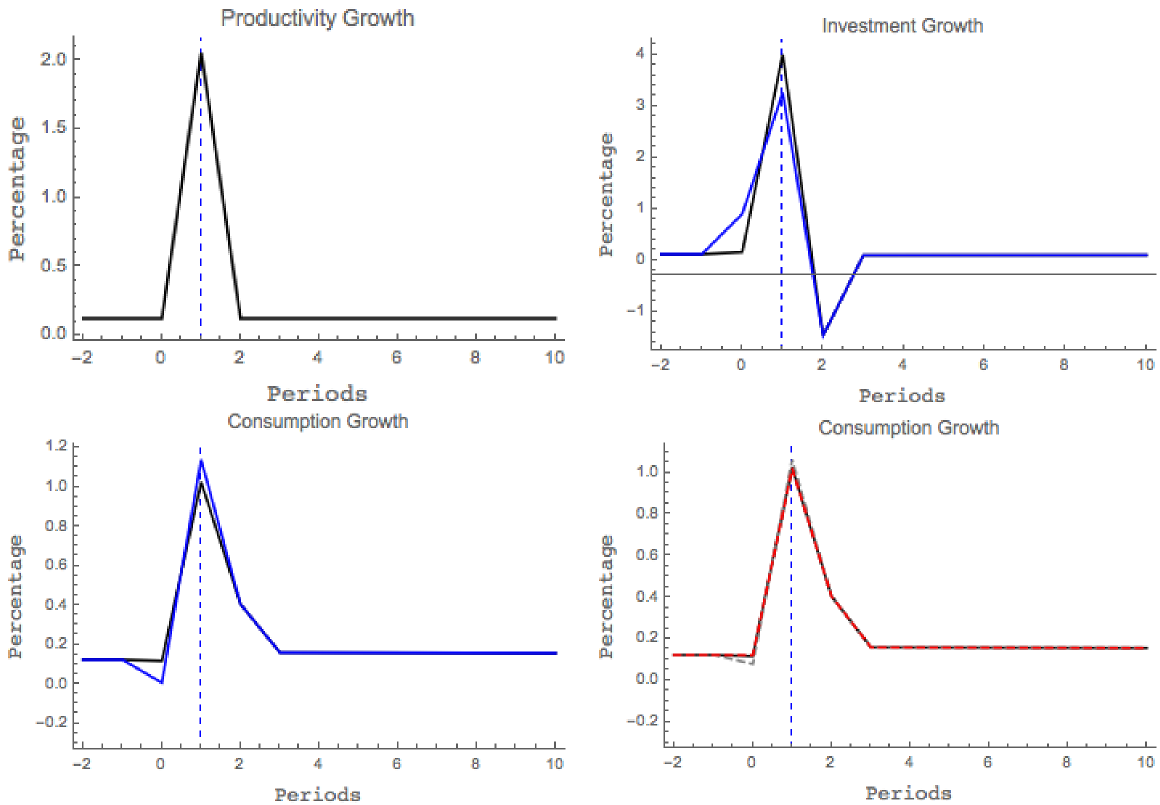
Notes: The figure presents the IRF for a 2 standard deviation shock on η^L that materializes in period 1. The upper-left panel presents the shock. The upper-right panel presents the price of capital in the economy. The lower-left panel shows the risk-free rate and the lower-right panel presents the levered excess return. The black lines show the IRF for the benchmark economy and the blue ones for the fully rational economy. The dashed vertical lines show the time at which the shock is realized.

Figure 12: **Impulse response functions for η^L: cross-section**



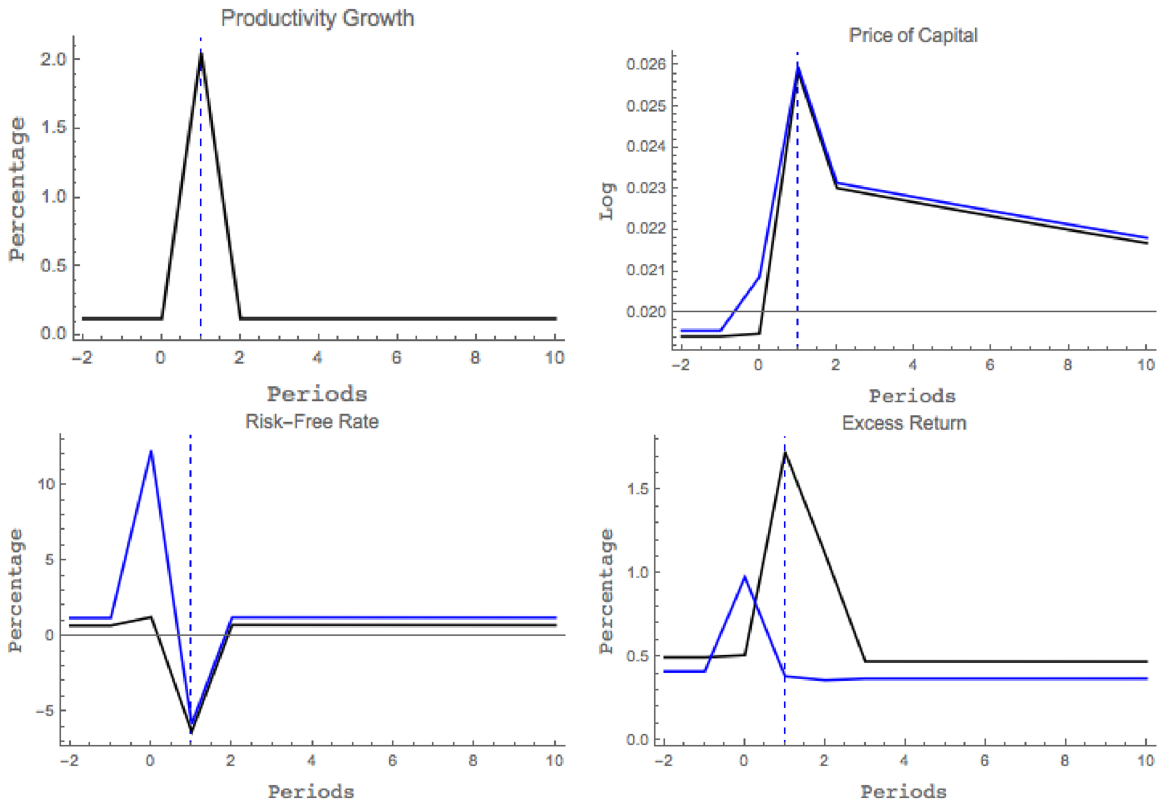
Notes: The figure presents the IRF for a 2 standard deviation shock on η^L that materializes in period 1. The upper-left panel presents the share in risky asset for the better-informed household. The upper-right panel presents the share in risky asset for the worse-informed household. The lower-left panel shows the return to net worth difference between households and the lower-right panel presents the wealth shares, the red dotted line in this panel corresponds to the worse-informed agent.

Figure 13: **Impulse response functions for η^S: real sector**



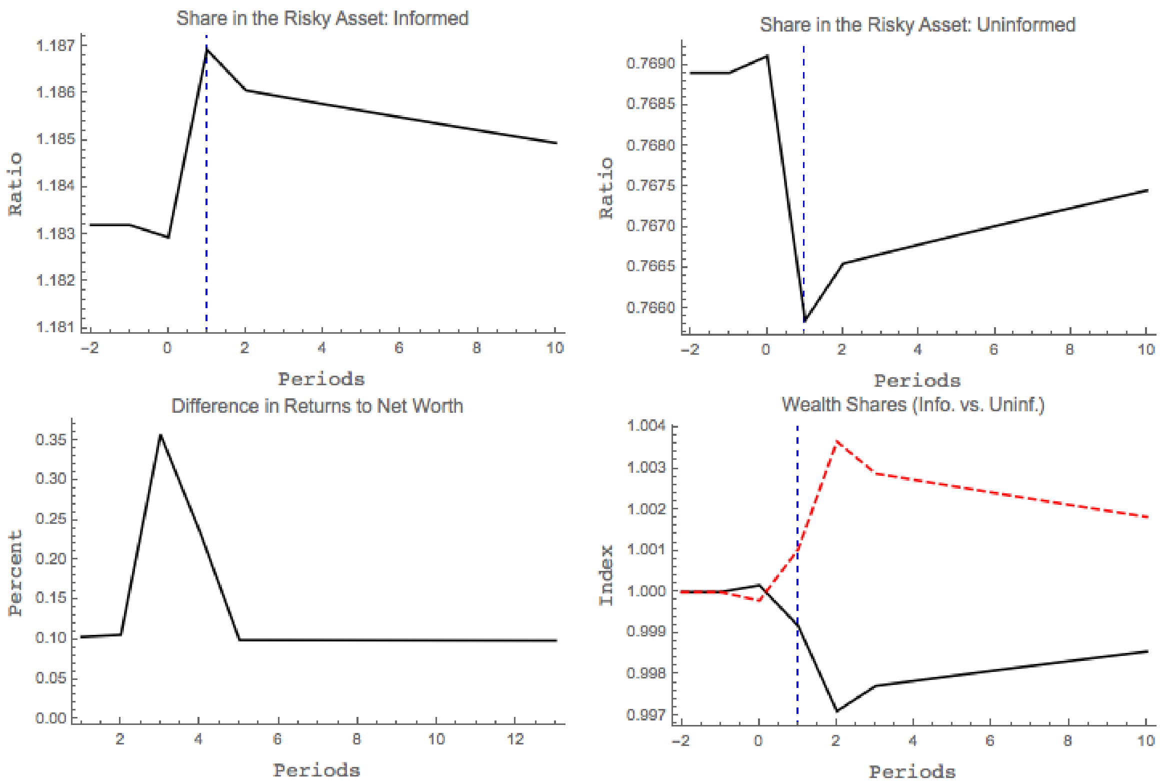
Notes: The figure presents the IRF for a 2 standard deviation shock on η^S that materializes in period 1. The upper-left panel presents the shock. The upper-right panel presents the investment growth rate. The lower-left panel shows the aggregate consumption growth rate and the lower-right panel presents consumption growth rate for each representative household. The black lines show the IRF for the benchmark economy and the blue ones for the fully rational economy. The dashed vertical lines show the time at which the shock is realized.

Figure 14: **Impulse response functions for η^S: financial sector**



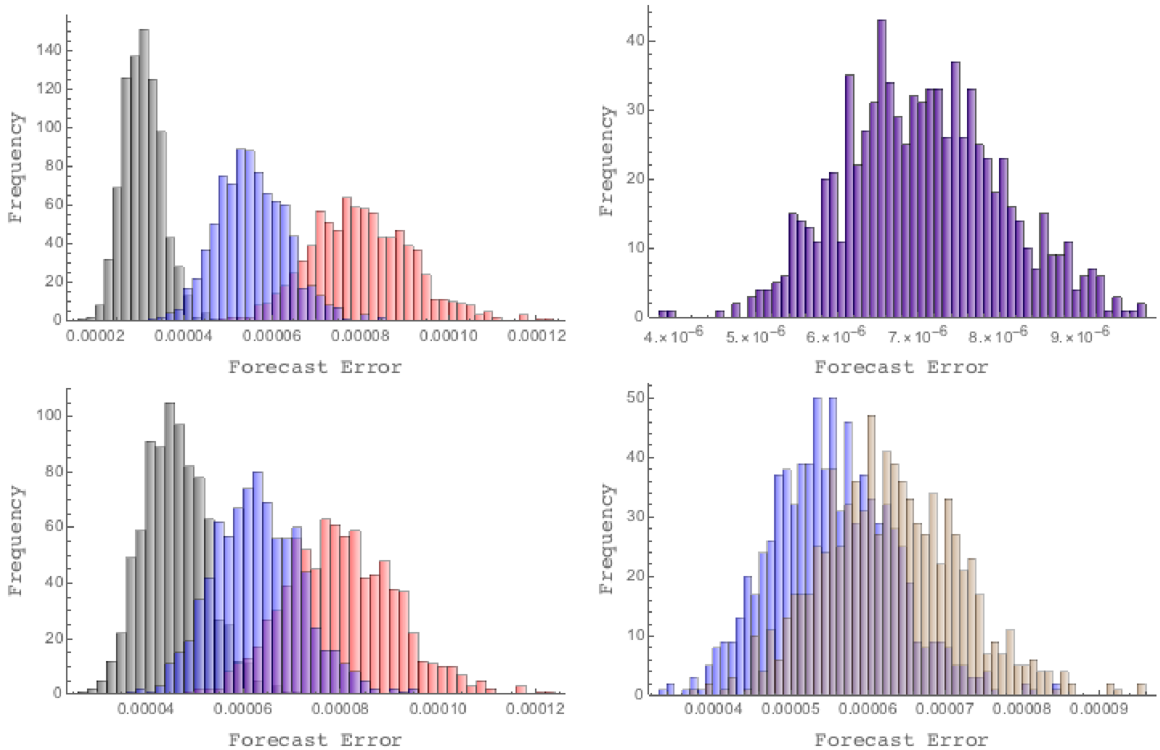
Notes: The figure presents the IRF for a 2 standard deviation shock on η^S that materializes in period 1. The upper-left panel presents the shock. The upper-right panel presents the price of capital in the economy. The lower-left panel shows the risk-free rate and the lower-right panel presents the levered excess return. The black lines show the IRF for the benchmark economy and the blue ones for the fully rational economy. The dashed vertical lines show the time at which the shock is realized.

Figure 15: **Impulse response functions for η^S: cross-section**



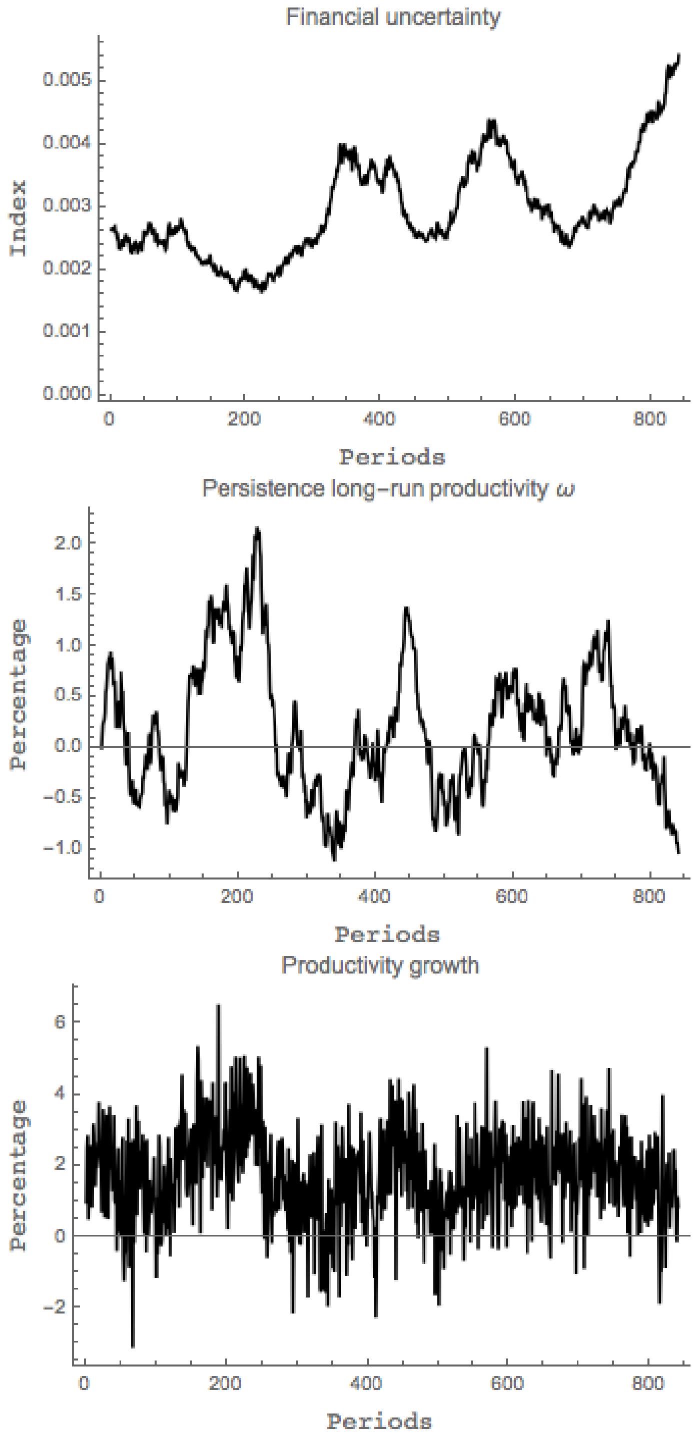
Notes: The figure presents the IRF for a 2 standard deviation shock on η^S that materializes in period 1. The upper-left panel presents the share in risky asset for the better-informed household. The upper-right panel presents the share in risky asset for the worse-informed household. The lower-left panel shows the return to net worth difference between households and the lower-right panel presents the wealth shares, the red dotted line in this panel corresponds to the worse-informed agent.

Figure 16: **One-step ahead forecast errors for output growth**



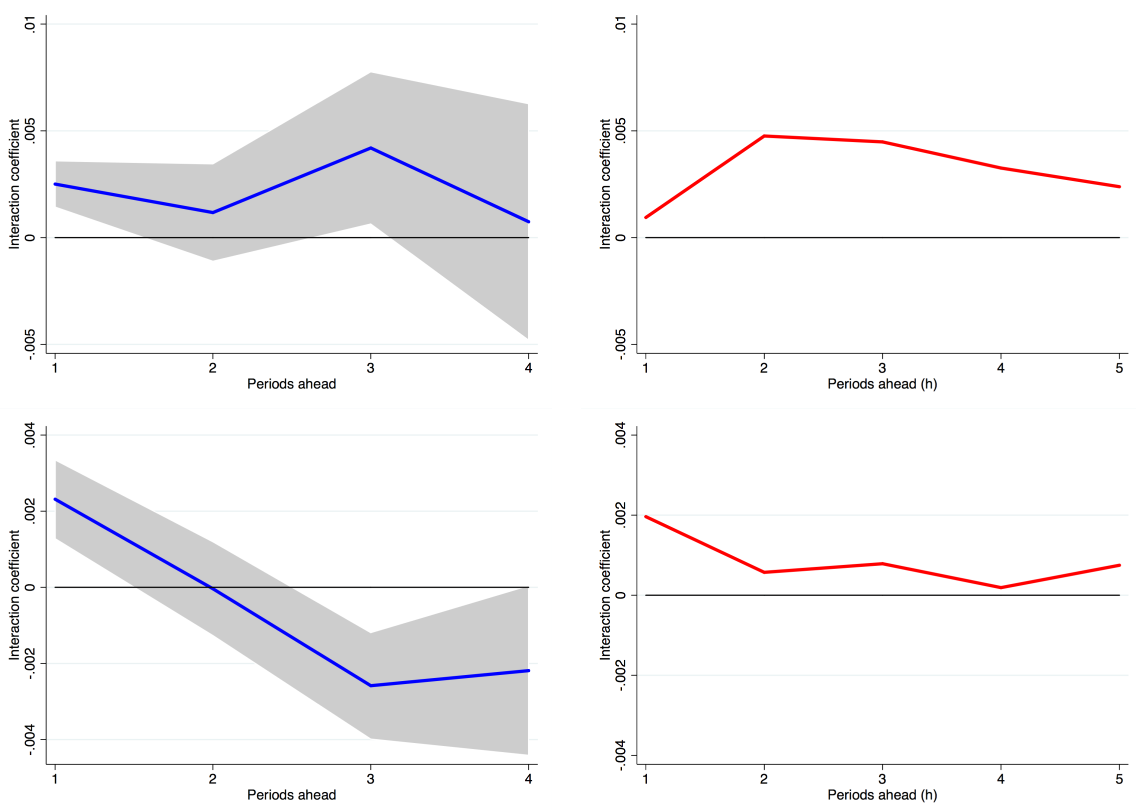
Notes: The figure reports the histogram of average forecast errors for the 100 simulations at each period of time. The upper-left panel presents the results for the benchmark calibration. The upper-right panel presents the results for the fully rational economy, the lower-left panel shows the results for the economy with aggregate noise in the private signal and the lower-right panel presents the cross-sectional average forecast errors for the benchmark calibration and the econmy with aggregate noise in private signals. The gray bars refer to the better-informed household, the red bars refers to the worse-informed household, and the blue bars reports the cross-section average forecast errors.

Figure 17: **One-period ahead financial uncertainty**



Notes: The upper panel of the figure reports the model-based financial uncertainty defined in equation 37 considering only the price of capital. The middle panel reports the annualized long-run productivity process ω in equation 11. The lower panel reports the annualized productivity growth in 10. The variables are obtained by averaging, in each period, the realizations for each of the 100 economies simulated. Correlation between financial uncertainty and long-run productivity process is -0.5. The correlation of uncertainty with productivity growth is -0.2.

Figure 18: **Local Projection Regressions**



Notes: The left-hand side panel present the local projection regressions coefficient of the interaction between uncertainty shocks and trading intensity using the PSID data. The right-hand-side panel presents the local projection regression coefficient γ_h using simulated data. The empirical model is $f_{jt+h} = \alpha_h + \beta_h I_{jt} + \gamma_h \left(e_t^F \# I_{jt}\right) + \varepsilon_{t+h}$ where f_{jt+h} denotes either returns to net worth or portfolio share on risky assets, I_{jt} is a categorical variable that takes value one for the better-informed household.

7. Tables

Table 1: **Summary statistics for different waves of the PSID**

	1989	**1994**	**1999**	**2001**	**2003**	**2005**	**2007**	**2009**	**2011**	**2013**	**2015**	**2017**
Ref Age	41.8	42.6	42.8	42.9	43.0	42.9	42.9	43.2	43.6	44.0	44.5	44.9
Spo Age	39.9	40.7	41.5	41.6	41.9	42.1	42.3	42.5	43.3	43.8	44.5	44.6
Ref Sex (%)	79.4	77.6	77.5	78.2	77.7	78.0	77.4	77.4	76.7	76.8	76.0	76.0
Num of members	2.7	2.7	2.7	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6	2.6
Num Children	0.9	0.9	0.8	0.8	0.7	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Ref Black (%)	8.9	8.5	8.1	8.4	8.2	9.4	9.2	9.6	9.7	9.9	10.1	10.4
Ref Spanish (%)	2.1	2.2	–	–	–	3.7	3.3	3.8	4.1	3.9	4.4	4.6
Spo Black (%)	3.6	2.8	2.8	2.9	2.5	2.7	2.8	3.0	2.9	2.7	2.7	2.6
Spo Spanish (%)	1.9	2.1	–	–	–	2.5	2.5	2.5	2.7	2.6	2.6	3.0
Own house (%)	63.5	64.6	65.2	64.7	65.4	65.2	62.8	61.4	60.4	58.4	58.0	58.7
Rent house (%)	32.0	31.5	30.2	30.6	30.0	30.0	32.5	33.3	34.7	36.1	37.0	36.4
Own stock (%)	30.2	35.5	37.0	39.1	36.4	35.5	35.3	33.6	30.9	30.1	28.4	28.9
Assets	**268935.0**	**262283.0**	**322234.0**	**338622.8**	**342076.4**	**372582.7**	**422033.8**	**362815.1**	**340236.1**	**318996.0**	**377218.8**	**382729.2**
Financial	59116.3	73014.2	104801.7	117551.5	106555.9	105956.9	116281.3	102132.6	113235.4	119016.8	135307.6	145457.0
CSB	30355.9	26124.6	19601.7	21442.5	21683.9	21282.2	23517.1	26346.1	22162.1	22677.4	24201.6	28527.2
Stock	23333.5	40397.1	45437.6	52791.2	47679.2	43632.3	45583.9	36371.4	39197.3	45207.9	48828.0	55152.4
IRA	0.0	0.0	34309.7	37723.7	32591.7	35189.6	42412.8	32655.9	45841.1	46871.6	56906.8	57723.1
Other	5426.8	6492.4	5452.7	5594.1	4601.2	5852.9	4767.4	6759.3	6034.9	4259.9	5371.2	4054.3
Non-Financial	209818.7	189268.8	217432.3	221071.3	235520.4	266625.8	305752.5	260682.5	227000.7	199979.2	241911.2	237272.1
House	126169.9	113768.0	127540.1	139367.4	152819.5	179863.0	188671.5	164575.7	147731.7	137085.1	146933.9	150991.9
Other Real Estate	40691.8	36955.1	31410.8	32689.6	37568.3	37733.3	50410.9	41445.1	29478.1	24399.5	30830.7	32172.3
Private Business	37530.2	32053.3	53028.8	43420.2	40531.5	43176.6	61902.7	47902.4	43756.0	34234.7	58775.4	50053.6
Other	5426.8	6492.4	5452.7	5594.1	4601.2	5852.9	4767.4	6759.3	6034.9	4259.9	5371.2	4054.3
Liabilities	**54309.2**	**59728.9**	**69975.9**	**73867.5**	**81791.8**	**92624.3**	**97011.0**	**98096.4**	**89177.2**	**82426.5**	**82987.8**	**82373.8**
House	47585.0	49531.2	60707.5	63181.6	71248.2	80280.7	83075.7	82641.3	75136.6	67947.3	66781.7	66720.8
Other	6724.3	10197.7	9268.4	10685.9	10543.6	12343.6	13935.3	15455.1	14040.6	14479.2	16206.1	15653.1
Net wealth	**214625.8**	**202554.1**	**252258.0**	**264755.3**	**260284.6**	**279958.5**	**325022.7**	**264718.8**	**251058.8**	**236569.5**	**294231.0**	**300355.3**
Income												
Ref Total	**10136.4**	**7492.6**	**8725.6**	**10005.4**	**10330.2**	**13188.4**	**12976.0**	**9422.3**	**8693.4**	**8399.1**	**9714.4**	**10159.9**
Ref Financial	2762.2	2033.2	2251.7	2305.3	2005.2	1362.9	2121.9	1503.9	1496.4	1732.5	2188.2	2136.4
Interest	0.0	913.4	728.6	777.8	510.0	329.9	544.1	531.4	317.9	387.9	325.2	269.0
Dividends	2762.2	901.5	1188.6	1062.0	933.3	542.4	802.2	623.4	845.8	808.9	1171.0	771.5
Royalties	0.0	51.3	113.8	260.3	284.8	160.1	277.8	123.9	127.7	138.2	166.9	374.7
Annuities/IRA	0.0	166.9	220.7	205.3	277.1	330.5	497.8	225.2	204.9	397.5	525.1	721.2
Ref Non-Financial	7374.2	5459.4	6473.9	7700.1	8325.1	11825.5	10854.2	7918.3	7197.0	6666.6	7526.2	8023.5
Rent (total)	6149.0	4301.3	5089.1	6008.9	6710.8	9339.5	9521.1	6539.8	5760.7	5740.1	6171.4	6723.0
Priv. Buss (assets)	1225.3	1158.2	1384.8	1691.2	1614.3	2486.0	1333.0	1378.5	1436.3	926.5	1354.8	1300.5
Spo Total	**7283.0**	**5371.9**	**6797.5**	**6105.1**	**8744.1**	**12077.9**	**11754.5**	**8773.6**	**7846.5**	**8067.8**	**8360.2**	**9792.0**
Spo Financial	551.3	931.8	259.8	332.2	397.5	727.3	795.2	547.3	648.2	1210.9	686.6	1480.3
Interest	0.0	28.1	63.5	95.7	61.6	223.8	321.2	233.7	180.6	403.7	149.9	281.9
Dividends	551.3	876.5	196.3	214.1	46.0	448.1	368.3	280.9	409.5	650.3	343.1	856.1
Royalties	0.0	27.2	0.0	22.5	290.0	55.4	105.8	32.7	58.1	19.1	38.5	136.5
Annuities/IRA	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	137.9	155.2	205.7
Spo Non-Financial	6731.7	4440.1	6537.7	5772.9	8346.6	11350.6	10959.2	8226.3	7198.3	6856.9	7673.6	8311.7
Rent (total)	5139.1	3895.6	4607.9	5527.7	6914.1	10244.9	10194.4	7059.7	6374.8	6218.1	6889.2	7803.9
Priv. Buss (assets)	1592.6	544.5	1929.9	245.2	1432.5	1105.7	764.8	1166.6	823.5	638.8	784.4	507.8
Payments												
Ref Total	**5488.8**	**6097.9**	**6680.9**	**7202.4**	**7182.4**	**7478.6**	**7971.6**	**7702.4**	**6991.9**	**6358.2**	**6374.7**	**6311.7**
Mortgage	4197.4	4110.5	4929.6	5162.2	5262.5	5501.6	5771.1	5440.7	5045.1	4448.3	4359.2	4420.0
Others	1291.4	1987.4	1751.2	2040.2	1919.9	1977.0	2200.5	2261.7	1946.9	1909.9	2015.5	1891.7
Spo Total	**6106.0**	**6691.7**	**7125.2**	**7555.3**	**7613.5**	**8053.0**	**8584.5**	**8141.2**	**7641.8**	**6857.4**	**6948.7**	**6783.9**
Mortgage	4882.5	4646.5	5679.7	5930.6	6072.7	6260.3	6645.1	6244.0	6012.1	5359.8	5361.1	5285.8
Others	1223.5	2045.2	1445.5	1624.7	1540.8	1792.8	1939.4	1897.3	1629.7	1497.6	1587.5	1498.0

Notes: The table presents summary statistics for several waves of the PSID. Wealth variables are provided at the household level. Income variables are provided at the reference person and spouse level.

Table 2: **Returns for different asset categories**

Wealth Component	Mean	St. Dev.	P10	Median	P90
Net worth	0.021	0.194	-0.151	0.023	0.209
Financial Wealth	0.052	0.198	0.002	0.045	0.291
CSB	0.031	0.046	0.000	0.011	0.091
Stocks	0.099	0.215	0.004	0.064	0.235
Non-Financial Wealth	0.080	0.346	-0.134	0.069	0.398
Housing	0.071	0.197	-0.086	0.058	0.237
Private Business	0.117	1.001	-1.000	0.014	0.210

Notes: statistics for the estimated returns for different asset categories for the pooled dataset. See Appendix B for a definition of each asset category. The sample spans the period 1986 - 2017.

Table 3: **Portfolio composition**

	Gross wealth shares				Leverage ratio mort.	Log gross wealth
	Financial wealth		Non-financial wealth			
	CSB	Stocks	Housing	Pri. Bus.		
All households						
Btm. 10%	7.53	3.02	88.81	0.64	91.80	8.57
10-20%	7.07	2.15	89.89	0.89	82.93	7.60
20-50%	7.85	2.58	88.71	0.87	68.55	9.64
50-75%	10.42	7.31	79.67	2.60	41.25	11.62
75-90%	16.06	17.16	59.92	6.87	20.51	12.45
90-95%	17.47	26.38	44.09	12.06	11.98	13.11
Top 5%	13.22	34.71	22.40	29.67	3.97	13.99
Home owners						
Btm. 10%	3.65	1.76	94.39	0.20	97.57	11.15
10-20%	2.92	1.24	95.18	0.66	87.81	10.75
20-50%	4.38	1.54	93.54	0.54	72.28	10.89
50-75%	9.01	6.27	82.48	2.24	42.71	11.66
75-90%	15.30	16.47	61.77	6.46	21.14	12.45
90-95%	17.26	25.68	45.46	11.60	12.35	13.12
Top 5%	13.00	34.41	23.01	29.58	4.08	13.99
Renters						
Btm. 10%	69.25	23.09	0.00	7.65	0.00	6.88
10-20%	77.64	17.58	0.00	4.78	0.00	6.17
20-50%	71.45	21.62	0.00	6.93	0.00	7.51
50-75%	50.38	36.81	0.00	12.81	0.00	11.06
75-90%	40.62	39.37	0.00	20.02	0.00	12.24
90-95%	24.39	48.91	0.00	26.70	0.00	13.01
Top 5%	21.42	45.70	0.00	32.88	0.00	13.97

Notes: PSID implied portfolio composition for the pooled dataset. Households are sorted by net wealth. The share of home owners in the pooled dataset is 70%. See Appendix B for a definition of each asset category. The sample spans the period 1986 - 2017.

Table 3b: **Portfolio composition (renters)**

	Gross wealth shares				Leverage ratio mort.	Log gross wealth
	Financial Wealth		Non-financial Wealth			
	CSB	Stocks	Housing	Pri. Bus.		
Btm.10%	69.25	23.09	0.00	7.65	0.00	6.88
10-20%	77.64	17.58	0.00	4.78	0.00	6.17
20-50%	71.45	21.62	0.00	6.93	0.00	7.51
50-75%	50.38	36.81	0.00	12.81	0.00	11.06
75-90%	40.62	39.37	0.00	20.02	0.00	12.24
90-95%	24.39	48.91	0.00	26.70	0.00	13.01
Top 5%	21.42	45.70	0.00	32.88	0.00	13.97

Notes: PSID implied portfolio composition for the pooled dataset. See Appendix B for a definition of each asset category. The sample spans the period 1986 - 2017.

Table 4: **Results for the Empirical Model**

Variables	(1)	(2)	(3)
Stocks share	0.0291***	0.0339***	0.0337***
	(0.007)	(0.007)	(0.007)
Housing share	0.0306***	0.0373***	0.0371***
	(0.006)	(0.006)	(0.006)
Private business share	0.102***	0.122***	0.119***
	(0.007)	(0.008)	(0.008)
Debt share	-0.025***	-0.031***	-0.025***
	(0.005)	(0.004)	(0.005)
Fin. Unc. Shock		-0.041*	-0.040*
		(0.021)	(0.021)
No Active trading			-0.008***
			(0.003)
No Active trading, bottom 80%			-0.030***
			(0.004)
Active trading, bottom 80%			-0.039***
			(0.004)
Demographics (Age, Education)	Y	Y	Y
Year and state effects	Y	Y	Y
Shares*Year effects	Y	Y	Y
Wealth effects	Y	Y	Y
R^2	0.201	0.220	0.221
Observations	64,716	64,716	64,716
Number of idividuals	9,113	9,113	9,113

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The sample spans the period 1986 - 2017.

Table 5: **Externally set parameters**

Parameter	Symbol	Value	Source/Comments
		Household Sector	
Intertemporal elasticity of substitution	ψ	2	Croce (2014)
Consumption share	χ	0.20	Croce (2014)
Share of agents acquiring information	λ	12%	See the text
		Final Good Sector	
Capital share	α	0.34	
AC long-run risk	ρ^{12}	0.80	Croce (2014)
Long-run volatility	$\sqrt{12}\sigma_{\eta L}$	0.33%	Hassan and Mertens (2017), $\frac{\sigma_{\eta L}}{\sigma_{\eta S}} = 0.11$
		Investment Sector	
Capital adjustment cost slope	ν_1	$(\delta + e^{\mu} - 1)^{\frac{1}{\xi}}$	$\Psi(\cdot) = 0$, $\Psi'(\cdot) = 0$ in deterministic steady-state
Capital adjustment cost intercept	ν_0	$\frac{1}{1-\xi}(\delta + e^{\mu} - 1)$	$\Psi(\cdot) = 0$, $\Psi'(\cdot) = 0$ in deterministic steady-state
		Information Parameters	
Near-rational errors			
Long-run	$\frac{\sigma_{\varepsilon L}}{\sigma_{\eta L}}$	0.09%	Hassan and Mertens (2017)
Short-run	$\frac{\sigma_{\varepsilon S}}{\sigma_{\eta S}}$	0.42%	Hassan and Mertens (2017)
Aggregate noise in private signals			
Long-run	$\frac{\sigma_{\zeta L}}{\sigma_{\eta L}}$	0.50	
Short-run	$\frac{\sigma_{\zeta S}}{\sigma_{\eta S}}$	1.00	
Private signal precision: better-informed household			
Long-run	$\frac{\sigma_{iL}}{\sigma_{\eta L}}$	23.6	Hassan and Mertens (2017)
Short-run	$\frac{\sigma_{iS}}{\sigma_{\eta S}}$	13.6	Hassan and Mertens (2017)

Notes: Externaly set parameters are standard in the literature or can be observed directly from the data. For the information parameters, I used the benchmark estimation in Hassan and Mertens (2017).

Table 6: **Calibrated Parameters**

Parameter	Symbol	Value	Moment	Data	Model
		Household Sector			
Discount factor	β^{12}	0.95	$\mathbb{E}[r^f]$	0.78%	0.79%
Relative risk aversion	γ	10.5	$\mathbb{E}[r_{ex}^{Lev}]$	4.82%	4.88%
		Final Good Sector			
Depreciation rate	12δ	5.0%	$\mathbb{E}\left[\frac{\exp(x)}{\exp(y)}\right]$	17.48%	27.3%
Average productivity	12μ	1.47%	$\mathbb{E}[dy]$	1.47%	1.47%
Short run volatility	$\sqrt{12}\sigma_{\eta S}$	3.34%	$\sigma[dy]$	4.02%	3.89%
		Investment Sector			
Capital adjustment cost	ξ	6.0	$\sigma(dx)$	7.08%	6.92%
		Information Parameters			
Private signal precision: worse-informed household					
Long-run	$\frac{\sigma_{uL}}{\sigma_{\eta L}}$	0.82	$(dy - E[dy])^2$	0.08%	0.05%
Short-run	$\frac{\sigma_{uL}}{\sigma_{\eta L}}$	0.98	$\frac{(dy-E_i[dy])^2}{(dy-E_j[dy])^2}$	0.036	0.038
		Cross-sectional Moments			
Steady-state Bond Holdings	b_{jss}	8.18	$\frac{\lambda(q_{ss}k_{iss}+b_{iss})}{(1-\lambda)\left(q_{ss}k_{jss}+b_{jss}\right)}$	1.44	1.44
Steady-state Capital Holdings	k_{jss}	19.95	$\frac{(1-\lambda)q_{ss}k_{jss}}{q_{ss}k_{ss}}$	0.33	0.33

Notes: Column Data resports the target moments. Statistics are calculated using annual data. Lower case variables denote logs. $d(\cdot)$ stands for the log-difference; for instance, dy is the output log-difference (or output growth). $E(\cdot)$ and $\sigma(\cdot)$ denote mean and standard deviation, respectively. All variables are expressed in per-capita terms. In the data the sample spans the period 1948-2015. For the model, I simulate the economy 100 times for 840 periods with a burning sample of 200 periods to reduce the effect of initial conditions when computing the model's implied moments.

Table 7: **Untargeted Moments**

Moment	Data	Model
$\sigma(r^f)$	2.32%	1.15%
$\sigma(r_{ex}^{Lev})$	18.86%	13.28%
$\sigma(dc)$	3.92%	3.79%
ACF(r^f)	0.57	0.55
ACF(r_{ex}^{Lev})	-0.01	0.00
ACF(dc)	0.47	0.68
corr(dc, di)	0.50	0.46
corr(dc, r_{ex}^{Lev})	0.05	0.08

Notes: Column Data resports the untargeted moments. Statistics are calculated using annual data. Lower case variables denote logs. $d(\cdot)$ stands for the log-difference; for instance, dy is the output log-difference (or output growth). $E(\cdot)$, $\sigma(\cdot)$, ACF$(\cdot)$, and corr$(\cdot,\cdot)$ denote mean, standard deviation, first-order autocorrelation, and correlations, respectively. All variables are expressed in per-capita terms. In the data the sample spans the period 1948-2015. For the model, I simulate the economy 100 times for 840 periods with a burning sample of 200 periods to reduce the effect of initial conditions when computing the model's implied moments.

Table 8: **Simulated Moments for Different Information Assumptions**

Variable	Benchmark Economy	Rational Economy	Aggregate Noise Economy
	Information Side		
$\sigma_{\eta L}$	0.11%	0.11%	0.11%
$\sigma_{\eta S}$	0.97%	0.97%	0.97%
$\frac{\sigma_{\varepsilon L}}{\sigma_{\eta L}}$	0.09%	0%	0.09%
$\frac{\sigma_{\varepsilon S}}{\sigma_{\eta S}}$	0.42%	0%	0.42%
$\frac{\sigma_{iL}}{\sigma_{\eta L}}$	23.66	23.66	23.66
$\frac{\sigma_{iS}}{\sigma_{\eta S}}$	13.83	13.83	13.83
$\frac{\sigma_{uL}}{\sigma_{\eta L}}$	94.66	94.66	94.66
$\frac{\sigma_{uS}}{\sigma_{\eta S}}$	55.31	55.31	55.31
$\frac{\sigma_{\xi}}{\sigma_{\eta L}}$	0.00	0.00	0.50
$\frac{\sigma_{\xi}}{\sigma_{\eta S}}$	0.00	0.00	1.00
$\frac{\mathbb{V}_i\left[\eta^L\right]}{\sigma_{\eta L}}$	0.50	0.00	0.58
$\frac{\mathbb{V}_i\left[\eta^S\right]}{\sigma_{\eta S}}$	0.52	0.00	0.63
$\frac{\mathbb{V}_u\left[\eta^L\right]}{\sigma_{\eta L}}$	0.82	0.00	0.82
$\frac{\mathbb{V}_u\left[\eta^S\right]}{\sigma_{\eta S}}$	0.98	0.00	0.98
	Asset Pricing Moments		
$\mathbb{E}[r^f]$	0.79%	1.25%	0.78%
$\sigma(r^f)$	1.15%	1.99%	1.15%
$\mathbb{E}[r_{ex}^{Lev}]$	4.88%	3.94%	5.0%
$\sigma(r_{ex}^{Lev})$	13.28%	12.32%	13.6%
ACF(r^f)	0.55	0.52	0.55
ACF(r_{ex}^{Lev})	0.00	0.00	0.00
corr(dc, r_{ex}^{Lev})	0.08	-0.12	0.09
	Micro Moments		
$\mathbb{E}[(r_i - r_u)]$	1.02%	0.68%	0.99%
$\sigma[(r_i - r_u)]$	0.59%	0.43%	0.58%
ACF$[(r_i - r_u)]$	0.30	-0.34	0.29
$\mathbb{E}[\mathrm{ws}_i]$	56.4%	55.0%	56.7%
$\mathbb{E}[\mathrm{sR}_i]$	1.17	1.20	1.16
$\mathbb{E}[\mathrm{sR}_u]$	0.78	0.82%	0.79
$\frac{(dy-E_i[dy])^2}{(dy-E_u[dy])^2}$	38.3%	100.0%	57.3%

Notes: Lower case variables denote logs. $d(\cdot)$ stands for the log-difference; for instance, dy is the output log-difference (or output growth). $E(\cdot)$, $\sigma(\cdot)$, ACF$(\cdot)$, and corr$(\cdot,\cdot)$ denote mean, standard deviation, first-order autocorrelation, and correlations, respectively. ws$_j$ refers to wealth share for household j and sR$_j$ is the share on risky asset (capital) for household j. I simulate the economy 100 times for 840 periods with a burning sample of 200 periods to reduce the effect of initial conditions when computing the model's implied moments.

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Appendix

A. Additional model details and proofs

A.1 Static Model

TBA

A.2 Dynamic Model

This section presents the solution of the dynamic model. I start by solving the households' problem, then I show how to scale the economy to get a stationary representation of the model. This section also presents the results for the information structure in the model.

Household sector: Households have Epstein and Zin (1989) preferences over consumption and leisure. Let $v_{jt}(S_t, k_{jt-1}, b_{jt-1})$ be the value function of a household j that start the period t with an aggregate state S_t and individual states $\{k_{jt-1}, b_{jt-1}\}$. Each household solves the following problem

$$\max_{\{c_{jt},k_{jt},b_{jt},l_{jt}\}} v_{jt}(S_t, k_{jt-1}, b_{jt-1}) = \left((1-\beta)\, \tilde{c}_{jt}^{1-\frac{1}{\psi}} + \beta \mathcal{E}_{jt} \left[(v_{jt+1}(S_{t+1}, k_{jt}, b_{jt}))^{1-\gamma^j} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma^j}} \right)^{\frac{1}{1-\frac{1}{\psi}}}$$

s.t.

$$c_{jt} + q_t k_{jt} + q_t^f b_{jt} + \Psi_j^b(b_{jt}) = w_t l_{jt} + n_{jt-1} + T_{jt} + H_{jt}$$

$$\tilde{c}_{jt} = c_{jt}^{\chi} \left(z_{t-1} \left(1 - l_{jt}\right)\right)^{1-\chi}$$

$$n_{jt-1} = \frac{1}{\lambda^j} \mathrm{ws}_{jt} q_{t-1} R_t k_{t-1}$$

$$\mathrm{ws}_{jt} = \lambda_j \frac{q_{t-1} R_t k_{jt-1} + b_{jt-1}}{q_{t-1} R_t k_{t-1}}$$

$$\Psi_j^b\left(b_{jt}\right) = q_t^f z_t \frac{\psi_j^b}{2} \left(\frac{b_{jt}}{z_t} - b_{jss} \right)^2$$

First, I take derivative with respect to bond holdings. Note that the model presents bond adjustment costs. These are necesary to ensure the existence of a well-defined deterministic steady state.

The first-order condition is given by

$$\Bigg[\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}\left(-\psi_j^b\left(\frac{b_{jt}}{z_t}-b_{jss}\right)-1\right)q_t^f$$

$$+\beta\left(\mathcal{E}_{jt}\left(v_{jt+1}(b_{jt},k_{jt})\right)^{1-\gamma^j}\right)^{\frac{\gamma^j-1/\psi}{1-\gamma^j}}\mathcal{E}_{jt}\left[\left(v_{jt+1}(b_{jt},k_{jt})\right)^{-\gamma^j}v_{jb,t+1}\right]\Bigg]=0 \qquad (A.1)$$

Next, I take derivative with respect to capital holdings. In this case, the first-order condition is given by

$$\Bigg[-\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}q_t$$

$$+\beta\left(\mathcal{E}_{jt}\left(v_{jt+1}(b_{jt},k_{jt})\right)^{1-\gamma^j}\right)^{\frac{\gamma^j-1/\psi}{1-\gamma^j}}\mathcal{E}_{jt}\left[\left(v_{jt+1}(b_{jt},k_{jt})\right)^{-\gamma^j}v_{jk,t+1}\right]\Bigg]=0 \qquad (A.2)$$

The envelope conditions for bonds and capital are

$$v_{jb,t}=(v_{jt})^{1/\psi}\left[-\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}\right]$$

$$v_{jk,t}=(v_{jt})^{1/\psi}\left[\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}\left(d_t+(1-\delta)q_t\right)\right]$$

Using the ebvelope conditions I obtain the Euler equations for bond and capital holdings. Note that in the case of bond holdings I defined the gross risk-free rate as the inverse of the price of the risk-free bond; that is, $R_t^f=\frac{1}{q_t^f}$. The Euler equation for bond holdings is

$$1=\mathcal{E}_{jt}\left[\beta\left(\frac{v_{jt+1}}{\left(\mathcal{E}_{jt}\left(v_{jt+1}\right)^{1-\gamma^j}\right)^{\frac{1}{1-\gamma^j}}}\right)^{1/\psi-\gamma^j}\left(\frac{c_{jt+1}}{c_{jt}}\right)^{-1}\left(\frac{(c_{jt+1})^{\chi}\left(z_t(1-l_{jt+1})\right)^{1-\chi}}{(c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}}\right)^{1-\frac{1}{\psi}}\frac{R_t^f}{1-\psi_j^b\left(\frac{b_{jt}}{z_t}-b_{jss}\right)}\right]$$

In the case of capital holdings, the Euler equation is given by

$$1=\mathcal{E}_{jt}\left[\beta\left(\frac{v_{jt+1}}{\left(\mathcal{E}_{jt}\left(v_{jt+1}\right)^{1-\gamma^j}\right)^{\frac{1}{1-\gamma^j}}}\right)^{1/\psi-\gamma^j}\left(\frac{c_{jt+1}}{c_{jt}}\right)^{-1}\left(\frac{(c_{jt+1})^{\chi}\left(z_t(1-l_{jt+1})\right)^{1-\chi}}{(c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}}\right)^{1-\frac{1}{\psi}}R_{t+1}\right]$$

Note that one can define the stochastic discount factor (SDF) for agent j as follows

$$\mathcal{M}_{j,t,t+1}=\beta\left(\frac{v_{jt+1}}{\left(\mathcal{E}_{jt}\left(v_{jt+1}\right)^{1-\gamma^j}\right)^{\frac{1}{1-\gamma^j}}}\right)^{1/\psi-\gamma^j}\left(\frac{c_{jt+1}}{c_{jt}}\right)^{-1}\left(\frac{(c_{jt+1})^{\chi}\left(z_t(1-l_{jt+1})\right)^{1-\chi}}{(c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}}\right)^{1-\frac{1}{\psi}} \qquad (A.3)$$

Hence, the Euler equations for bonds and capital holdings are

$$1=\mathcal{E}_{jt}\left[\mathcal{M}_{j,t,t+1}\frac{R_t^f}{1-\psi_j^b\left(\frac{b_{jt}}{z_t}-b_{jss}\right)}\right] \qquad (A.4)$$

$$1=\mathcal{E}_{jt}\left[\mathcal{M}_{j,t,t+1}R_{t+1}\right] \qquad (A.5)$$

Finally, I get the intra-temporal condition for labor. Taking derivative with respect to labor in the above problem I obtain

$$\frac{w_t}{z_{t-1}} = \frac{1-\chi}{\chi} \frac{c_{jt}}{z_{t-1}(1-l_{jt})} \tag{A.6}$$

Production sector: The production sector consist of two representative firms, a final good producer and a capital producer. The final good producer will rent capital and pay for labor services from the household sector. Given that the final good producer does not take any investment decision and it only rents services from an existing capital stock, its problem becomes the standard period-by-period maximization problem. The first order conditions of the final good producer defines the wage and the rental rate of physical capital

$$w_t = (1-\alpha)\, z_t^{1-\alpha} \left(\frac{k_{t-1}}{l_t}\right)^{\alpha} \tag{A.7}$$

$$r_t^k = \alpha z_t^{1-\alpha} \left(\frac{k_{t-1}}{l_t}\right)^{\alpha-1} \tag{A.8}$$

The second firm in the economy is the capital investment firm. The final good producers owns this investment firm which produces physical capital in the economy paying quadratic adjustment costs. The firm takes the price of capital as given and then seeks to maximize profits. The first order condition defines the price of capital

$$q_t = \frac{1}{1-\Psi'\left(\frac{x_t}{k_{t-1}}\right)} \tag{A.9}$$

profits per-unit of capital stock k_{t-1} are

$$\pi_t^x = q_t \left(\Psi'\left(\frac{x_t}{k_{t-1}}\right)\frac{x_t}{k_{t-1}} - \Psi\left(\frac{x_t}{k_{t-1}}\right)\right) \tag{A.10}$$

Market clearing: Prices in the economy clear four markets (i) the labor market, (ii) the capital rental market, (iii) the capital claims market, and (iv) tje bond market

$$l_t = \sum_j \lambda^j l_{jt} \tag{A.11a}$$

$$k_t = \sum_j \lambda^j k_{jt} \tag{A.11b}$$

$$k_t = (1-\delta)\, k_{t-1} + x_t + \Psi\left(\frac{x_t}{k_{t-1}}\right) k_{t-1} \tag{A.11c}$$

$$0 = \sum_j \lambda^j b_{jt} \tag{A.11d}$$

A.2.1 Stationary economy

The productivity process in the model is not stationary, hence I need to scale the variables in the model to get a balanced growth path. The scaling factor for variables at period t is z_{t-1}. Let tilde variables $(\tilde{\cdot})$ denote stationary variables in the model which are obtained by scaling households and firms' optimal conditions, resource constraints, and market clearing condition. Then, to make variables stationary I use the following rules

$$\tilde{c}_{jt} \equiv \frac{c_{jt}}{z_{t-1}} \quad \tilde{x}_t \equiv \frac{x_t}{z_{t-1}}, \quad \tilde{w}_t \equiv \frac{w_t}{z_{t-1}}, \quad \tilde{b}_{jt} \equiv \frac{b_{jt}}{z_t}, \quad \tilde{k}_{jt} \equiv \frac{k_{jt}}{z_t}, \quad \tilde{k}_t \equiv \frac{k_t}{z_t},$$
$$\tilde{v}_{jt} \equiv \frac{\frac{v_{jt}}{z_{t-1}}}{\left(\frac{c_{jt}}{z_{t-1}}\right)^{\chi}(1-l_{jt})^{1-\chi}}, \tag{A.12}$$

Household sector: Given this notation, I start with the household certainty equivalence function which is equal to

$$\frac{ce_{jt}}{\left(z_{t-1}(\tilde{c}_{jt})^{\chi}(1-l_{jt})^{1-\chi}\right)^{1-\gamma^j}} = e^{(1-\gamma^j)\Delta z_t}\mathcal{E}_{jt}\left(\tilde{v}_{jt+1}\frac{(\tilde{c}_{jt+1})^{\chi}(1-l_{jt+1})^{1-\chi}}{(\tilde{c}_{jt})^{\chi}(1-l_{jt})^{1-\chi}}\right)^{1-\gamma^j}$$
$$\tilde{ce}_{jt} = \mathcal{E}_{jt}\left(e^{\Delta z_t}\tilde{v}_{jt+1}\left(\frac{\tilde{c}_{jt+1}}{\tilde{c}_{jt}}\right)^{\chi}\left(\frac{1-l_{jt+1}}{1-l_{jt}}\right)^{1-\chi}\right)^{1-\gamma^j} \tag{A.13}$$

Next, define $\widehat{\mathcal{E}}_{jt}$ as the following transformation of the expected utility

$$\widehat{\mathcal{E}}_{jt} = \mathcal{E}_{jt}\left(\tilde{v}_{jt+1}(\tilde{c}_{jt+1})^{\chi}(1-l_{jt+1})^{1-\chi}\right)^{1-\gamma^j} \tag{A.14}$$

Given this transformation, the utility value in equilibrium can be computed using the following expression

$$\left(\tilde{v}_t^i\right)^{1-\frac{1}{\psi}} = (1-\beta) + \beta\left[e^{(1-\gamma^j)\Delta z_t}\frac{\widehat{\mathcal{E}}_{jt}}{\left((\tilde{c}_{jt})^{\chi}(1-l_{jt})^{1-\chi}\right)^{1-\gamma^j}}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma^j}} \tag{A.15}$$

Given this expressions, household j's SDF in the stationary economy is given by the following expression

$$\tilde{\mathcal{M}}_{j,t,t+1} = \beta e^{-\frac{\Delta z_t}{\psi}}\left(\frac{e^{\Delta z_t}\tilde{v}_{jt+1}\left(\frac{\tilde{c}_{jt+1}}{\tilde{c}_{jt}}\right)^{\chi}\left(\frac{1-l_{jt+1}}{1-l_{jt}}\right)^{1-\chi}}{(\tilde{ce}_{jt})^{\frac{1}{1-\gamma^j}}}\right)^{1/\psi-\gamma^j}\left(\frac{\tilde{c}_{jt+1}}{\tilde{c}_{jt}}\right)^{-1}\left(\frac{(\tilde{c}_{jt+1})^{\chi}(1-l_{jt+1})^{1-\chi}}{(\tilde{c}_{jt})^{\chi}(1-l_{jt})^{1-\chi}}\right)^{1-\frac{1}{\psi}} \tag{A.16}$$

Then, I need to express the Euler equations in terms of the stationary economy. Since prices, besided the wage rate, are stationary, one only needs to replace the SDF by its version in the stationary economy

$$1 = \mathcal{E}_{jt}\left[\tilde{\mathcal{M}}_{j,t,t+1}\frac{R_t^f}{1-\psi_j^b\left(\tilde{b}_{jt}-b_{jss}\right)}\right] \tag{A.17}$$

$$1 = \mathcal{E}_{jt}\left[\tilde{\mathcal{M}}_{j,t,t+1}R_{t+1}\right] \tag{A.18}$$

The intra-temporal condition for labor is similar to the one in the non-stationary economy. In particular, it becomes

$$\tilde{w}_t = \frac{1-\chi}{\chi}\frac{\tilde{c}_{jt}}{1-l_{jt}} \tag{A.19}$$

Finally, the budget constraint in the stationary economy is given by

$$\tilde{c}_{jt} + e^{\Delta z_t}q_t\tilde{k}_{jt} + e^{\Delta z_t}q_t^f b_{jt} + e^{\Delta z_t}q_t^f\frac{\psi_j^b}{2}\left(\tilde{b}_{jt}-b_{jss}\right)^2 = \tilde{w}_t l_{jt} + q_{t-1}R_t\tilde{k}_{jt-1} + \tilde{b}_{jt-1} + \tilde{T}_{jt} + \tilde{H}_{jt} \tag{A.20}$$

Note that after aggregating within households and across households, we obtaint the resouce constraint.

$$\lambda\tilde{c}_{it} + e^{\Delta z_t}q_t\lambda\tilde{k}_{it} + e^{\Delta z_t}q_t^f\lambda b_{it} + e^{\Delta z_t}q_t^f\lambda\frac{\psi_i^b}{2}\left(\tilde{b}_{it}-b_{iss}\right)^2 = \tilde{w}_t\lambda l_{it} + q_{t-1}R_t\lambda\tilde{k}_{it-1} + \lambda\tilde{b}_{it-1} + \lambda\tilde{T}_t$$

$$\begin{aligned}(1-\lambda)\tilde{c}_{ut} + e^{\Delta z_t}q_t(1-\lambda)\tilde{k}_{ut} + e^{\Delta z_t}q_t^f(1-\lambda)b_{ut} + e^{\Delta z_t}q_t^f(1-\lambda)\frac{\psi_u^b}{2}\left(\tilde{b}_{ut}-b_{uss}\right)^2 &= \tilde{w}_t(1-\lambda)l_{ut} \\ + q_{t-1}R_t(1-\lambda)\tilde{k}_{ut-1} + (1-\lambda)\tilde{b}_{ut-1} + (1-\lambda)\tilde{T}_t&\end{aligned}$$

where I use the fact that the portfolio costs are distributed across households given the measure λ

$$\sum_j \tilde{T}_{jt} = \lambda_j\tilde{T}_t = \sum_j \lambda_j e^{\Delta z_t}q_t^f\frac{\psi_j^b}{2}\left(\tilde{b}_{jt}-b_{jss}\right)^2$$

Then, adding these constraints using the law of motion for capital and the fact that the production function is homogeneous of degree one, I get the following resource constraint

$$\tilde{c}_t + \tilde{x}_t = \tilde{y}_t \tag{A.21}$$

Production sector: the optimal conditions of both firms in the production sector are the same. I note that the production function, the wage rate, the capital rental rate, and the capital law of motion are the only equations that change in the stationary economy

$$\tilde{y}_t = e^{(1-\alpha)\Delta z_t} \tilde{k}_{t-1}^{\alpha} l_t^{1-\alpha} \tag{A.22}$$

$$\tilde{w}_t = (1-\alpha)\, e^{(1-\alpha)\Delta z_t} \left(\frac{\tilde{k}_{t-1}}{l_t} \right)^{\alpha} \tag{A.23}$$

$$r_t^k = \alpha e^{(1-\alpha)\Delta z_t} \left(\frac{l_t}{\tilde{k}_{t-1}} \right)^{1-\alpha} \tag{A.24}$$

$$e^{\Delta z_t} \tilde{k}_t = (1-\delta)\, \tilde{k}_{t-1} + \tilde{x}_t - \Psi \left(\frac{\tilde{x}_t}{\tilde{k}_{t-1}} \right) \tilde{k}_{t-1} \tag{A.25}$$

Finally, returns for the risk-free bond and the physical capital are the following ones

$$R_t^f = \frac{1}{q_t^f} \tag{A.26}$$

$$R_t \equiv \frac{(d_t + (1-\delta) q_t)}{q_{t-1}} \tag{A.27}$$

Model equations: The state variables in the model are (i) the aggregate capital stock at the beginning of period t (k_{t-1}), (ii) the capital holdings of the better-informed household at the beginning of period t (k_{it-1}), the bond position of the better-informed at the beginning of period t (b_{it-1}), the long-term component of the labor productivity shock ω_{t-1}, the period t realization of the long and shor-term productivity shocks (η_t^L and η_t^S), the aggregate expecations for the long and short-run productivity shocks ($\bar{\mathbb{E}}_t^L$ and $\bar{\mathbb{E}}_t^S$). Denote the aggregate state vector as $S_t = \{k_{t-1}, k_{it-1}, b_{it-1}, \omega_{t-1}, \eta_t^L, \eta_t^S, \bar{\mathbb{E}}_t^L, \bar{\mathbb{E}}_t^S\}$. In addition, better and worse-informed representative agents within each household have individual state variables given by $S_{jt} = \{S_t, \mathcal{E}_{jt}[\eta_{t+1}^L], \mathcal{E}_{jt}[\eta_{t+1}^S]\}$ where the last two elements of the vector are given by the conditional expectations of each household. Note that with this notation, one can express the model equations as follows

$$f_1(S_{jt}) = \mathcal{E}_{jt}\left[f_2(S_{jt}, S_{jt+1}) \right] \tag{A.28}$$

The model equations are

$$
\begin{aligned}
\tilde{w}_t &= \frac{1-\chi}{\chi}\frac{\tilde{c}_{jt}}{1-l_{jt}} \\
1 &= \mathcal{E}_{jt}\left[\tilde{\mathcal{M}}_{j,t,t+1}\frac{1/q_t^f}{1-\psi_j^b\left(\tilde{b}_{jt}-b_{jss}\right)}\right] \\
1 &= \mathcal{E}_{jt}\left[\tilde{\mathcal{M}}_{j,t,t+1}R_{t+1}\right] \\
\tilde{ce}_{jt} &= \mathcal{E}_{jt}\left(e^{\Delta z_t}\tilde{v}_{jt+1}\left(\frac{\tilde{c}_{jt+1}}{\tilde{c}_{jt}}\right)^{\chi}\left(\frac{1-l_{jt+1}}{1-l_{jt}}\right)^{1-\chi}\right)^{1-\gamma^j} \\
\widehat{\mathcal{E}}_{jt} &= \mathcal{E}_{jt}\left(\tilde{v}_{jt+1}\left(\tilde{c}_{jt+1}\right)^{\chi}\left(1-l_{jt+1}\right)^{1-\chi}\right)^{1-\gamma^j} \\
\left(\tilde{v}_t^i\right)^{1-\frac{1}{\psi}} &= (1-\beta)+\beta\left[e^{(1-\gamma^j)\Delta z_t}\frac{\widehat{\mathcal{E}}_{jt}}{\left(\left(\tilde{c}_{jt}\right)^{\chi}\left(1-l_{jt}\right)^{1-\chi}\right)^{1-\gamma^j}}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma^j}} \\
\tilde{c}_{jt}+e^{\Delta z_t}q_t\tilde{k}_{jt}+e^{\Delta z_t}q_t^f b_{jt}+e^{\Delta z_t}q_t^f\frac{\psi_j^b}{2}\left(\tilde{b}_{jt}-b_{jss}\right)^2 &= \tilde{w}_t l_{jt}+q_{t-1}R_t\tilde{k}_{jt-1}+\tilde{b}_{jt-1}+\tilde{T}_{jt} \\
c_t &= \sum_j \lambda^j c_{jt} \\
l_t &= \sum_j \lambda^j l_{jt} \\
k_t &= \sum_j \lambda^j k_{jt} \\
0 &= \sum_j \lambda^j b_{jt}
\end{aligned}
$$

Note that I can express the prices in these equations (w_t, R_t, q_t) as function of the variables in the above system. So, I get a system of 18 unkowns on 18 equations.

A.2.2 Conditional Expectations and Average Expectations

Given Proposition 1 and Assumption 2, households infer $\overline{\mathbb{E}}_{jt}^k = \int \mathbb{E}_{jt}\left[\eta_{t+1}^k\right]dj + \varepsilon_t^k$ from prices. To ease notation, I will not make explicit the productivity shock index k since the procedure for both is the same. The key point in the signal extraction problem is that households do not need all the state variable but only their average expectation. Then, one has the following conditions

$$\mathbb{E}_{jt}\left[\eta_{t+1}\right] = \mathbb{E}\left[\eta_{t+1}|s_{jt},S_t\right] = \mathbb{E}\left[\eta_{t+1}|s_{jt},\overline{\mathbb{E}}_{jt}\right]$$

Then, one can guess a linear function for the rational expectation

$$\mathbb{E}_{jt}\left[\eta_{t+1}\right] = \alpha_{j0}+\alpha_{j1}s_{jt}+\alpha_{j2}\overline{\mathbb{E}}_{jt} \tag{A.29}$$

α's are the coefficients for the prior, private signal and average expectation. Recall that the private signal is given by

$$s_{jt} = \eta_{t+1} + e_t^F + \sigma_{jt}\epsilon_{jt} \tag{A.30}$$

Using (A.29)-(A.30) and integrating, I get

$$\int \mathbb{E}_{jt}\left[\eta_{t+1}\right] di = \alpha_0 + \alpha_1\left(\eta_{t+1} + e_t^F\right) + \alpha_2 \overline{\mathbb{E}}_{jt}$$
$$\overline{\mathbb{E}}_{jt} = \alpha_{j0} + \alpha_{j1}\left(\eta_{t+1} + e_t^F\right) + \alpha_{j2}\overline{\mathbb{E}}_{jt} + \varepsilon_t$$

Then, the average expectation of household of type j is

$$\overline{\mathbb{E}}_{jt} = \frac{\alpha_{j0}}{1-\alpha_{j2}} + \frac{\alpha_{j1}}{1-\alpha_{j2}}\eta_{t+1} + \frac{\alpha_{j1}}{1-\alpha_{j2}}e_t^F + \frac{1}{1-\alpha_{j2}}\varepsilon_t \tag{A.31}$$

Next, I guess and verify that the solution for the average expectation $\overline{\mathbb{E}}_{jt}$ is some linear function of η, e^F, and ε, then

$$\overline{\mathbb{E}}_{jt} = \pi_{j0} + \pi_{j1}\eta_{t+1} + \pi_{j2}e_t^F + \pi_{j3}\varepsilon_t \tag{A.32}$$

matching coefficients one gets

$$\pi_{j0} = \frac{\alpha_{j0}}{1-\alpha_{j2}} \qquad \pi_{j1} = \pi_{j2} = \frac{\alpha_{j1}}{1-\alpha_{j2}} \qquad \pi_{j3} = \frac{1}{1-\alpha_{j2}}$$

With these expressions, note that the vector $\{\eta_{t+1}, s_{jt}, \overline{\mathbb{E}}_{jt}\}$ has the following distribution

$$\begin{bmatrix}\eta_{t+1}\\ s_{jt}\\ \overline{\mathbb{E}}_{jt}\end{bmatrix} \sim N\left(\begin{bmatrix}0\\0\\ \pi_{j0}\end{bmatrix}, \begin{bmatrix}\sigma_\eta^2 & \sigma_\eta^2 & \pi_{j1}\sigma_\eta^2\\ \sigma_\eta^2 & \sigma_\eta^2+\sigma_e^2+\sigma_{jt}^2 & \pi_{j1}\sigma_\eta^2+\pi_{j2}\sigma_e^2\\ \pi_{j1}\sigma_\eta^2 & \pi_{j1}\sigma_\eta^2+\pi_{j2}\sigma_e^2 & \pi_{j1}\sigma_\eta^2+\pi_{j2}\sigma_e^2+\pi_{j3}\sigma_\varepsilon^2\end{bmatrix}\right) \tag{A.33}$$

Using the Bayes theorem one obtains a system of equations that depends on π's and the deep parameters of the model (the variance of the shocks). Finally, the conditional mean and conditional variance are used as states in the solution of the dynamic model.

A.2.3 Proof of Proposition 1

The proof of this proposition follows the one in Hassan and Mertens (2017). Note form the above discussion that one can group the equilibrium equations in the model as follow

$$f_1\left(S_{jt}\right) = \mathcal{E}_{jt}\left[f_2\left(S_{jt}, S_{jt+1}\right)\right]$$

where

$$S_{jt} = \{k_{t-1}, k_{it-1}, b_{it-1}, \omega_{t-1}, \eta_t^L, \eta_t^S, \bar{\mathbb{E}}_{jt}^L, \bar{\mathbb{E}}_{jt}^S, \mathcal{E}_{jt}[\eta_{t+1}^L], \mathcal{E}_{jt}[\eta_{t+1}^S]\}$$

the functions $f_1(\cdot)$ and $f_2(\cdot,\cdot)$ are analytic, constinuously differentiable. I'm using the fact that $S_t \subset S_{jt}$ when taking the conditional expectation; however, when deriving the individual optiomal variables (consumption, labor, bond and capital), one needs to take into account over which information set each agent conditions the elements in S_{jt+1}. The functions $f_1(S_{jt})$ for $j = \{i,u\}$ are the solution to the system of equations. This means that one needs to show that $\mathcal{E}_{jt}\left[f_2\left(S_{jt}, S_{jt+1}\right)\right]$ is only a function of S_{jt}. I use Taylor's theorem and the properties of multivariate distribution. Note that one can approximate $f_2(\cdot,\cdot)$ as follows

$$
\begin{aligned}
& f_2\left(S_{jt}, k_t, k_{it}, b_{it}, \omega_t, \eta^L_{t+1}, \eta^S_{t+1}, \bar{\mathbb{E}}^L_{jt+1}[\eta^L_{t+2}], \bar{\mathbb{E}}^S_{jt+1}[\eta^S_{t+2}], \mathcal{E}_{jt+1}[\eta^L_{t+2}], \mathcal{E}_{jt+1}[\eta^S_{t+2}]\right) \\
&\quad = \sum_{\boldsymbol{k}} \frac{f_{\boldsymbol{k}}\left(S_{jt}\right)}{\boldsymbol{k!}} \left(k_t - k_{ss}\right)^{k_1} \left(k_{it} - k_{iss}\right)^{k_2} \left(b_{it} - b_{iss}\right)^{k_3} \left(\omega_t\right)^{k_4} \left(\eta^L_{t+1}\right)^{k_5} \left(\eta^S_{t+1}\right)^{k_6} \times \\
&\qquad\qquad \times \left(\bar{\mathbb{E}}^L_{jt+1}\right)^{k_7} \left(\bar{\mathbb{E}}^S_{jt+1}\right)^{k_8} \left(\mathcal{E}^L_{jt+1}\right)^{k_9} \left(\mathcal{E}^S_{jt+1}\right)^{k_{10}}
\end{aligned}
$$

The above expression denotes a general approximation. The next step is to take the conditional expectation of $f_2(\cdot,\cdot)$. Note that the variables k_t, k_{it}, b^s_{it}, and ω_t are known at t and hence will not be affected by the expectation. The terms $\bar{\mathbb{E}}^L_{jt+1}$, $\bar{\mathbb{E}}^S_{jt+1}$, $\mathcal{E}^L_{jt+1}$, and $\mathcal{E}^S_{jt+1}$ are distributed as i.i.d. normal variables; hence, it is unpredictable for households at period t and since all shocks are uncorrelated with each other, the terms with $k_7, \cdots, k_{10} = 1$ are zero and terms $k_7, \cdots, k_{10} > 1$ are known moments of the unconditional normal distribution and only depend on the mean and variance. Therefore, one can write the above equation as follow

$$
\begin{aligned}
& \mathcal{E}_{jt}\left[f_2\left(S_{jt}, k_t, k_{it}, b_{it}, \omega_t, \eta^L_{t+1}, \eta^S_{t+1}, \bar{\mathbb{E}}^L_{jt+1}[\eta^L_{t+2}], \bar{\mathbb{E}}^S_{jt+1}[\eta^S_{t+2}], \mathcal{E}_{jt+1}[\eta^L_{t+2}], \mathcal{E}_{jt+1}[\eta^S_{t+2}]\right)\right] \\
&\quad = \sum_{k=0}^{\infty}\sum_{h=0}^{\infty} \frac{\hat{f}_{kh}\left(S_{jt}, k_t, k_{it}, b_{it}, \omega_t\right)}{k!h!} \mathcal{E}_{jt}\left[\left(\eta^L_{t+1}\right)^k \left(\eta^S_{t+1}\right)^h\right] \\
&\quad = \sum_{k=0}^{\infty}\sum_{h=0}^{\infty} \frac{\hat{f}_{kh}\left(S_{jt}, k_t, k_{it}, b_{it}, \rho\omega_t + \eta^S_t\right)}{k!h!} \mathcal{E}_{jt}\left[\eta^L_{t+1}\right] \mathcal{E}_{jt}\left[\eta^S_{t+1}\right]
\end{aligned}
$$

the coefficients $\hat{f}_{kh}$ collects all the higher unconditional moments of $\bar{\mathbb{E}}^L_{jt+1}$, $\bar{\mathbb{E}}^S_{jt+1}$, $\mathcal{E}^L_{jt+1}$, and $\mathcal{E}^S_{jt+1}$. Note that the third line follows from the fact that productivity shocks are independent from each other and the fact that higher order moments are constant and we can include them with the coefficients $\hat{f}_{kh}$. Therefore, the above equation shows that the individual states for the representative agent within each household is given by S_{jt}.

The next step on the proof is to show that aggregate quantities and prices depend on the commonly known state variables S_t. To do this, denote an aggregate variable by $\overline{f}_1$, hence the any general variable for the representative household will be obtained by aggregating across all agentes that belong to this household

$$\overline{f}_1\left(S_t\right) = \int f_1\left(S_{jt}\right) dj = \int \sum_{k=0}^{\infty}\sum_{h=0}^{\infty} \frac{\hat{f}_{kh}\left(S_{jt}, k_t, k_{it}, b_{it}, \rho\omega_t + \eta_t^S\right)}{k!h!} \mathcal{E}_{jt}\left[\left(\eta_{t+1}^L\right)^k\right] \mathcal{E}_{jt}\left[\left(\eta_{t+1}^S\right)^h\right] dj$$

$$= \sum_{k=0}^{\infty}\sum_{h=0}^{\infty} \frac{\hat{f}_{kh}\left(S_{jt}, k_t, k_{it}, b_{it}, \rho\omega_t + \eta_t^S\right)}{k!h!} \int \mathcal{E}_{jt}\left[\left(\eta_{t+1}^L\right)^k\right] dj \int \mathcal{E}_{jt}\left[\left(\eta_{t+1}^S\right)^h\right] dj$$

For the long-run aggregate term (the sample applies for the short-run term)

$$\int \mathcal{E}_{jt}\left[\left(\eta_{t+1}^L\right)^k\right] dj = \int \mathcal{E}_{jt}\left[\left(\eta_{t+1}^L - \bar{\mathbb{E}}_{jt}^L + \bar{\mathbb{E}}_{jt}^L\right)^k\right] dj$$

$$= \sum_{h=0}^{k} \binom{k}{h} \left(\bar{\mathbb{E}}_{jt}^L\right)^{k-h} \int_0^1 \left(\alpha_{1j}\epsilon_{jt}\right)^h dj = \sum_{h=0}^{k} \binom{k}{h} \left(\bar{\mathbb{E}}_{jt}^L\right)^{k-h} \mathbb{E}\left(\alpha_{1j}\epsilon_{jt}\right)^h$$

This shows that the last two terms only depend on the aggregate average expectations and the terms in $\mathbb{E}\left(\alpha_{1j}\epsilon_{jt}\right)^h$ which are known since ϵ_{jt} is normally distributed.

B. Data

B.1 Macroeconomic Data

Labor: Labor is obtained from the National Income and Product Accounts (NIPA) annual data reoirted by the Bureau of Economic Analysis (BEA). I use the total number of full-time and part-time employees reported in line 1 of the Table 6.4. The data are in annual frequency.

Per-capita Consumption: Aggregate consumption is obtained from NIPA tables. It is in billions of dollars and at a quarterly frequency. To obtain annual measures, I sum the four quarters of a year. It is contructed by adding the nondurable consumption in line 5 of Table 1.1.5 and the consumption in services in line 6 of Table 1.1.5. Each of this items is expressed in real terms using the corresponding price deflators. For consumption it is the nondurable consumption price deflator in line 5 of Table 1.1.9 and for services it is in line 6 of the same table. Then, the real consumption is divided by the measure of labor above to obtain the per-capita consumption.

Per-capita Investment: Aggregate investment is obtained from NIPA tables. It is in billions of dollars and at a quarterly frequency. To obtain annual measures, I sum the four quarters of a year. It is contructed by substracting the information processing eequipment (which is interpreted as investment in intangible capital) in line 3 of Table 5.5.5 from fixed investment in line 8 of Table 1.1.5. Each element is deflated using the fixed investment deflator in line 8 of Table 1.1.9. Then, the real investment is divided by the measure of labor to obtain the per-capita consumption.

Per-capita Output: The model does not present a government sector and it is a closed economy. Therefore, per-capita output in the data is the sum of per-capita consumption and investment. I do this to bring the data moments to those computed using the model economy.

Real Risk-free Rate: The nominal risk-free rate the annual average of the 3-Month Treasury bill (secondary market rate) obtained through FRED with code DTB3. Then, to get the real rate I use the log change of the annual average of the Consumer Price Index (for all urban consumers: all items in U.S. city) also through FRED with code CPIAUCSL. The real rate is the nominal rate minus the CPI realized inflation.

Stock Market Return: The stock market return is obtained from the Fama-French dataset available at Kenneth French's webpage (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). I use the annual stock market return and substract from it the CPI inflation. The market excess return is obtained by substracting from the real market return the real risk-free rate.

B.2 Panel Study of Income Dynamics

The Panel Study of Income Dynamics (PSID) is a longitudinal household panel survey that began in 1968. The PSID was originally designed to study the dynamics of income and poverty. The 1968 PSID sample was drawn from two independent sub-samples: an over-sample of around 2000 low income families from the Survey of Economic Opportunity (SEO) and a nationally representative sample of around 3000 families designed by the Survey Research Center at the University of Michigan (SRC). These two sub-samples combined constitute a national probability sample of U.S. families as of 1968. Survey waves are annual from 1968 to 1997, and biennial since then.

I focus on the SRC sample which was initially representative of the US population. Because of this, the PSID does not provide wights for this sample. However, there is a concern about the representativeness of this survey since it may not capture appropriately the post-1968 inflow of immigrants to the United States (see Heathcote, Perri, and Violante (2010)).

In this section I describe the information used to construct the measures of returns in the paper. I start with asset and debt variables and then the income flows. The PSID asks about the following asset and liability categories:

- Business assets (W^{peq}_{bus}): *Do [you/you or anyone in your family] own part or all of a farm or business? If you sold all that and paid off any debts on it, how much would you realize on it?*
- Checking and savings (W^{saf}_{it}): *Do [you/you or anyone in your family] have any money in checking or savings accounts, money market funds, certificates of deposit, government savings bonds, or treasury bills; not including assets held in employer-based pensions or IRAs? If you added up all such [accounts/accounts for all of your family], about how much would they amount to right now?*
- Stocks (W^{sto}_{it}): *Do [you/you or anyone in your family] have any shares of stock in publicly held corporations, mutual funds, or investment trusts; not including stocks in employer-based pensions or IRAs? If you sold all that and paid off anything you owed on it, how much would you have?*

- IRAs and private annuities (W_{it}^{ira}): *Do [you/you or anyone in your family] have any money in private annuities or Individual Retirement Accounts (IRAs)? How much would they be worth?*

- House value (W_{it}^{hou}): *Do you (or anyone else in your family living there) own the (home/apartment)? Could you tell me what the present value of your (house/apartment) is; I mean about how much would it bring if you sold it today?*

- Net worth of real estate (W_{it}^{ore}): *Do [you/you or anyone in your family] have any real estate other than your main home, such as a second home, land, rental real estate, or money owed to you on a land contract? If you sold all that and paid off any debts on it, how much would you realize on it?*

- Net worth of vehicles (W_{it}^{veh}): *What is the value of what [you/you or anyone in your family] own on wheels? Including personal vehicles you may have already told me about and any cars, trucks, a motor home, a trailer, or a boat; what are they worth all together, minus anything you still owe on them?*

- Other assets (W_{it}^{oth}): *Do [you/you or anyone in your family] have any other savings or assets, such as bond funds, cash value in a life insurance policy, a valuable collection for investment purposes, or rights in a trust or estate that you haven't already told us about? If you sold that and paid off any debts on it, how much would you have?*

- Mortgage balances (D_{it}^{hou}): *Do you have a mortgage on this property (your primary residence)? About how much is the remaining principal on this mortgage (includes land contract, home equity, home improvement, line of credit loan)?*

- Other debt balances (D_{it}^{oth}): *Aside from the debts that we have already talked about, like any mortgage on your main home or vehicle loans, do [you/you or anyone in your family] currently have any other debts such as credit card charges, student loans, medical or legal bills, or loans from relatives? If you added up all these [debts/debts for all of your family], about how much would they amount to right now?*

From 2011 on, the PSID divides D_{it}^{oth} into the followjng categories:

- Credit card debt (D_{it}^{cca}): *If you added up all credit card and store card debts for (all of (your/the) familyliving there), about how much would they amount to right now?*

- Student loan debt (D_{it}^{stu}): *If you added up all student loans (for all of (your/the) family living there), about how much would they amount to right now?*

- Medical bills (D_{it}^{med}): *If you added up all medical loans (for all of your family living there), about how much would they amount to right now?*

- Legal bills (D_{it}^{med}): *If you added up all legal loans (for all of your family living there), about how much would they amount to right now?*

- Loans from relatives (D_{it}^{rel}): *If you added up all relatives loans (for all of your family living there), about how much would they amount to right now?*

- Unspecified other debt (D_{it}^{rel}): *If you added up all other loans (for all of your family living there), about how much would they amount to right now?*

From 2013 on, the PSID divides W_{it}^{ore} and W_{bus}^{peq} into the value of the real estate and farm and business separately from debt owed. To maintain homogeneity in the definitions across years, I continue with the aggregate definition of other debt (D_{it}^{oth}) and with the net measures (i.e. assets minus liabilities) for other real estate and private equity wealth.