Return Heterogeneity, Information Frictions, and Economic Shocks

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December, 2020

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Abstract

This study investigates the effects of information disparities on returns to net worth and their role in amplifying wealth inequality in the wake of big economic shocks. Using a panel of US individuals, I present new evidence that returns among individuals holding similar asset classes are heterogeneous in part because of how those individuals respond to economic shocks. Specifically, I show that individuals whom survey data suggest are better-informed earn significantly higher returns after big uncertainty shocks compared to less well-informed individuals. I investigate a potential channel to explain this outperformance. I show that better-informed wealthy investors hedge themselves better against uncertainty shocks by conducting a market-timing strategy. To interpret these facts, I build a dynamic, stochastic, general equilibrium economy in which individuals with near-rational expectations are heterogeneous in their private signals' quality about future fundamentals. I show that those with more precise information earn higher average returns because they are better equipped to hedge against endogenous uncertainty shocks using a market-timing strategy to exploit their more accurate information about future fundamentals. The model implies that disparities in the quality of information lead to higher wealth inequality.

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 four decades, there has been a significant increase in wealth inequality[1]. A contributor to this trend is the existence of heterogeneous returns on wealth. Empirically, it has been shown that individual characteristics and portfolio composition potentially explain the observed heterogeneity in returns[2]. However, there is no consensus on which of these two features is more important in explaining returns' heterogeneity. More importantly, little is known about the dynamic patterns in the heterogeneous returns. Theoretically, most studies propose an exogenous process for heterogeneity in returns and calibrate this process to match specific data moments[3]. This paper provides evidence and proposes a theory that links heterogeneity in returns to information frictions among investors. Specifically, using a panel of US individuals, I present new evidence that wealth returns among individuals holding similar asset classes are heterogeneous in part because of how those individuals respond to economic shocks. I show that individuals whom survey data suggests are better-informed earn significantly higher returns after large uncertainty shocks compared to less well-informed individuals. To interpret these facts, I build a dynamic, stochastic, general equilibrium economy with two sources of information frictions: incomplete information, and near-rationality.

The first part of this paper presents new empirical evidence that relates information disparities to heterogeneous returns. I use data from the Panel Study of Income Dynamics (PSID) to construct measures of returns for different asset categories and combine it with data from the University of Michigan's Surveys of Consumers (SOC) on exposure to news related to the stock market, credit conditions, and firms' profits. I use these SOC data to construct a proxy for how informed individuals are about financial markets.

[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, respectively.

[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 theoretical studies that propose micro-founded models that generate heterogeneity in returns and satisfactorily match the wealth distribution are Quadrini (2000), in which entrepreneurial opportunities allow wealthier households to save more, and Kaplan, Moll, and Violante (2018), in which transaction costs in higher return illiquid assets lead richer households to hold portfolios with higher returns.

I present the following empirical results. First, I show a positive relationship between risk-adjusted annual returns to net worth and wealth, which suggests a role for information in explaining this result. Second, I show that better-informed investors earn higher returns and that this informational advantage is significant in the face of adverse economic shocks. Third, I provide evidence on the persistence of this outperformance in time and a role for market-timing strategies.

I first provide evidence that returns to net worth and financial wealth correlate positively with an individual's position in the wealth distribution. This positive correlation remains when returns are adjusted for investors' idiosyncratic risk; that is, Sharpe ratios exhibit a positive relationship with wealth. This latter fact suggests that differences in risk-bearing capacity (another potential explanation for the observed diversity in returns) are not the only mechanism at play behind returns heterogeneity.

I then present novel cross-sectional facts on the role of information in explaining return heterogeneity. To do so, I estimate a panel data model to study the role of the proxy for informedness on returns to wealth. I find that better-informed investors earn around 1.0% higher annual returns to net worth. This value is robust to the inclusion of demographic controls, portfolio shares, and time and state fixed effects. Then, I study the relevance of information in hedging strategies against adverse economic shocks. I include the interaction between the measure of informedness and statistical financial uncertainty shocks[4] and find that better-informed individuals earn an additional 0.5% higher returns to net worth due to how they respond to uncertainty shocks. I add to this analysis by presenting results considering returns to financial wealth, including checkings, savings, bonds, and stocks. In this case, better-informed investors earn 2.2% higher annual returns to financial wealth and an additional 0.6% higher returns when confronting uncertainty shocks.

Finally, I study the persistence of the outperformance attributed to information disparities. To do so, I establish new empirical facts in a dynamic setting. I find that better-informed individuals can sustain around 0.2% higher returns to net worth and 0.4% higher returns

[4]The financial uncertainty shocks is obtained from Ludvigson, Ma, and Ng (forthcoming). These are identified structural shocks from a VAR which includes an index of financial uncertainty. This index is the average of the volatility of the unforecastable component of the future value of a large number of financial indicators.

on financial wealth than worse-informed investors. This difference remains for about four periods[5], after an adverse economic shock. I then present further evidence that a potential explanation for the observed dynamic pattern on returns is a market-timing strategy. When an adverse shock hits the economy, better-informed investors increase the stocks' share of their financial wealth and then reduce it in subsequent periods once stock prices start to recover. One potential concern is that individuals in the upper and lower part of the wealth distribution hold different portfolios within the broadly defined asset class portfolios available in the data. Therefore, I focus only on the top 20% of the wealth distribution whose portfolios are significantly less exposed to real estate, an asset with lower adjustment frequency. I show that for this subsample, better-informed individuals who declare adjustments in stocks between surveys earn higher returns, highlighting the role of market-timing.

To interpret these facts, I start by presenting a static general equilibrium model of noisy rational expectations and endogenous information acquisition in which wealthy agents choose to be better-informed about the future payoff of the risky asset. 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. The model implies that wealthier investors will spend more on getting better signals about future payoffs, thereby generating a positive relation between returns and wealth. The model also produces Sharpe ratios increasing in wealth. A central implication of the assumption that the information technology's cost is independent of the wealth level is that the marginal cost of information does not depend on the portfolio size. In contrast, the marginal benefit increases with size.

The static model provides an important insight: wealthier individuals acquire more information obtaining private signals with higher precision. Using this observation, I propose a dynamic heterogeneous-agents model with information frictions. In the model, two types of households coexist. Both receive private signals about the economy's fundamental shocks; 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 cannot infer all the economy's information through prices or quantities. Households in the model can invest in two types

[5]PSID surveys are conducted every two years; therefore, a period corresponds to two years.

of assets: capital and a risk-free bond. The model does a good job matching macroeconomic and financial moments in the data. In terms of cross-sectional moments, the model can reproduce the difference in returns between better and worse-informed agents and comes close to explaining the dispersion in returns between these two groups while highlighting the role of information disparities in increasing wealth inequality.

Then, I use the model to study its implications for the dynamic empirical facts discussed above. I construct an endogenous measure of financial uncertainty shocks using the methodology in Ludvigson, Ma, and Ng (forthcoming). Using this measure, I show that the better-informed household in the model can sustain persistent higher returns after a financial uncertainty shocks. Moreover, the model predicts that the better-informed household does so by adjusting the portfolio's composition to increase the share held in the risky asset after the price has declined, then decrease the share as the price recovers. Hence, the model supports the empirical observation that better-informed investors follow a market-timing strategy.

Related literature There is no shortage of theories that explain the observed wealth inequality. On the theoretical side, the mechanisms that potentially 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[6]. Of these three potential explanations, heterogeneous returns and returns that covary positively with wealth are the ones that best match the observed wealth inequality in the data. However, most studies take these mechanisms as exogenous and calibrate them to match the target inequality[7]. This paper proposes information frictions among individuals as micro-foundations to generate cross-sectional differences in returns.

On the empirical front, Fagereng, Guiso, Malacrino, and Pistaferri (2020), for Norway,

[6]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.

[7]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 allow 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.

and Bach, Calvet, and Sodini (2018), for Sweden, present evidence that returns are heterogeneous; however, they disagree on the key drivers of this heterogeneity. For the former, heterogeneity in sophistication and financial information are important factors. On the other hand, for the latter, the exposure to systematic risk is the critical driver for wealthy individuals' higher returns. Importantly, however, these authors do not use a direct measure of informedness in their analysis, a gap this study is designed to fill. Moskowitz and Vissing-Jørgensen (2002) study the returns to private and public equity in the United States, and Flavin and Yamashita (2002) analyze housing returns[8]. My paper extends the analysis of these studies by jointly studying these asset categories and the liability side. This extension allows me to estimate returns to net worth and to present cross-sectional results in a dynamic setting. I show that better-informed individuals obtain higher returns by conducting a market-timing strategy.

My paper is also related to the empirical literature that aims to measure information advantages or attention in the data. First, Guiso and Jappelli (2020) present evidence that investment in financial information increases with wealth, and average portfolio return is positively associated with investment in information; however, they find that the expected Sharpe ratios are negatively related to information (and therefore with wealth), consistent with overconfidence theories. I construct realized Sharpe ratios and show that they are positively related to wealth (similar with Calvet, Campbell, and Sodini 2007, Calvet, Campbell, and Sodini 2009). Second, Gargano and Rossi (2018) present 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 news, analyst coverage, and stocks trading volume and frequency, positively correlate with their measure of attention. I follow their lead and use declared exposure to information about financial markets as a proxy for informedness. My paper relates to Kacperczyk, Nieuwerburgh, and Veldkamp (2014), who propose a definition of skill for fund managers and present evidence of stock picking in booms and market-timing in recessions. They show that skilled fund managers outperform unskilled ones and passive benchmarks. In my pa-

[8]On housing returns, recent contributions include Landvoigt, Piazzesi, and Schneider (2015) and Giglio, Maggiori, Stroebel, and Weber (2015).

per, I present evidence of market-timing strategies for informed wealthy individuals. This strategy becomes relevant in the wake of financial uncertainty shocks, negatively correlated with business cycles.

On the theoretical side, my paper is related to three lines of research. First, it adds to studies that highlight the role of heterogeneous returns to wealth. A group of studies assumes an exogenous process for returns; for instance, Hubmer, Krusell, and Smith Jr (2019) propose a heterogenous-agent model in which returns' mean and standard deviation depend on individuals' wealth level. Benhabib, Bisin, and Luo (2019) conduct a quantitative analysis using an overlapping generations economy with idiosyncratic returns and argue that this is one of the main factors necessary for matching the wealth distribution[9]. In contrast to these studies, my paper proposes a two-asset economy with information frictions that endogenous generate heterogeneity in returns. The second group of studies presents theories that endogenously generate return heterogeneity: Kaplan, Moll, and Violante (2018) using transaction costs in the illiquid assets, and Quadrini (2000) with heterogeneous entrepreneurial opportunities. By contrast, my paper proposes differences in information as a critical mechanism to explain return heterogeneity and wealth inequality.

Second, this paper contributes to the research on market timing to respond to aggregate uncertainty shocks (e.g. Chien and Lustig 2010, Chien, Cole, and Lustig 2012, Kacperczyk, Nieuwerburgh, and Veldkamp 2014, Kacperczyk, Van Nieuwerburgh, and Veldkamp 2016). My model underlines the advantage of better-informed agents when the economy faces adverse economic shocks. Besides, my setup is dynamic, which allows me to show persistence in the outperformance of better-informed agents who hedge themselves against uncertainty shocks by adjusting the composition of financial wealth toward stocks when prices are low and then reduce this share when prices start to recover.

Finally, my paper contributes to the literature that stresses the importance of information frictions in increasing wealth inequality. First, I extend the analyses in Hassan and Mertens (2014) and Hassan and Mertens (2017) by introducing heterogeneity in the household sector[10]. In my model, two households coexist. They differ in their private signals'

[9]Other studies that highlight the role of return heterogeneity are Gabaix, Lasry, Lions, and Moll (2016) and Benhabib and Bisin (2018).

[10]The first part of the theoretical section of my paper presents an endogenous information acquisition model

precision[11]; hence, the model allows me to measure the information friction's impact on wealth inequality. In this sense, my work is close to Kacperczyk, Nosal, and Stevens (2019), who strengthen the relation between information disparities and capital income inequality.

The rest of the paper is structured as follows. Section 2 presents suggestive evidence on returns to net worth and the role of information in a dynamic setting. Section 3 sets up the quantitative model, the equilibrium definition, and calibration. Section 4 presents the results. Finally, Section 5 concludes.

2. Empirical Evidence

This section proposes that informed individuals earn higher returns on average, and they can hedge better against adverse economic shocks. I first describe the data sources I use to calculate returns to net worth and the measures of information and describe some returns and portfolio patterns observed in the data. I then present cross-sectional facts on returns to net worth and the portfolio of individuals. I mainly show that individuals assumed to be better-informed earn higher returns even after controlling other variables that may explain the outperformance. I then turn to a dynamic analysis by illustrating that informed individuals perform better persistently when adverse economic shocks hit the economy.

2.1 Data description

Panel Study of Income Dynamics (PSID). The PSID is a longitudinal household panel survey that began in 1968. Following Moskowitz and Vissing-Jørgensen (2002), I use the Survey Research Center at the University of Michigan (SRC) subsample which is a nationally representative sample of about 3,000 families. I use the PSID survey waves for the period 1986 to 2017. 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

similar to Verrecchia (1982), Peress (2004), Mihet (2019). Using this model, I highlight the importance of information disparities in explaining the positive relationship between returns and Sharpe ratios with wealth and the composition of portfolios.

[11] In the dynamic model, similar to Grossman and Stiglitz (1980), two groups of households have different precisions for their private signals. Unlike this paper, my work takes the measure of better and worse-informed households as given.

provides geographic identifiers; in particular, it provides fips state codes for each household interviewed. The survey also provides wealth estimates of checking, savings, and bonds (CSB), stocks, IRAs and private annuities, declared house value, declared value of private businesses, other real estate assets, and other assets (including bond funds, cash value in a life insurance policy, a valuable collection for investment purposes, or rights in a trust or estate). On the liability side, the PSID provides information about mortgage balances, and other debts (including credit card charges and student loans).

Moving on to the income variables, the survey provides information about the reference person and the spouse on income from: interest, dividends, trust funds and royalties, annuities, IRAs, and unincorporated businesses. The PSID asks about homeowners' self-reported rent. However, this information is only available in the 2017 wave. Imputed rent is an important component of household income. 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 house value and rent for homeowners in each state using the last survey wave; I then calculate the weighted (house value) average using properties with 2-12 rooms for each state; finally, I apply the national growth rate of the price-rent ratio for the previous years. I use these state-level ratios and the individual house value to compute a measure of imputed rent. The PSID does not provide information on stock and house capital gains, which turns to be very important in explaining saving behavior across the distribution[12]. Without other sources to obtain a measure of capital gains, I construct this variable as the difference between beginning and end-of-period wealth in stocks and housing. The PSID includes information on mortgage payments; however, it does not provide 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 payments on other types of debt.

[12]Fagereng, Blomhoff Holm, Moll, and Natvik (2019) use 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

Appendix C provides more information on these variables. Also, Table A.6 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. Following Fagereng, Guiso, Malacrino, and Pistaferri (2020), in the case of wealth variables, I assume an equal split between reference persons and their spouses.

Surveys of consumers (SOC) - University of Michigan: The SOC is a national survey statistically designed to be representative of all American households. Each month the SOC interviews a minimum of 500 individuals who answer around 50 core questions. These questions cover three areas of consumer sentiments: personal finances, business conditions, and buying conditions. It also provides demographic information such as respondent's age, region of residence, marital status, number of kids, and education level, among others. Moreover, the survey gives wealth demographics like home and stock ownership. My primary measure of information comes from this survey.

I merge the SOC with the PSID using demographic, income, and wealth variables. Specifically, for each year between 1986 to 2017, I look for individuals with the same age, sex, education level, marital status, number of kids, and state of residence. I complement these variables with wealth demographics using home and stocks ownership. Finally, I use income quintiles to better match individuals in both surveys. By doing this, I am able to relate the returns constructed using the PSID data with information variables I obtain from the SOC. Appendix C describes in more detail the set of variables from the SOC. In addition, the appendix presents information on the merging process with the PSID.

Information variables. In this paper, I investigate the role of information disparities as a potential source of return heterogeneity. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) explain that it is challenging to measure the benefits of better information in the data directly. For this reason, I construct two variables as proxies of better information and show that both produce similar results. I then present a model in which information frictions are a key ingredient in explaining the facts I discuss below. In doing this, I follow the literature on information choice models which suggests testing the model's predictions against the data.

I construct the first proxy of information using the SOC. The survey asks about news the respondent may have heard about changes in business conditions. In particular, I focus on the following question: *During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?* I build two measures of information using the answers for this question. The first one is a finer measure which identifies informed individuals if they have heard news related to the stock market (codes: 36 and 76). The second measure is broader since it adds individuals that may have heard about interest rate and firms' profits news (codes: 33, 35, 36, 73, 74, and 76). Figure 1 presents the distribution of respondents by income quintiles (the SOC does not provide information about the wealth distribution). As the figure suggests, among individuals who heard news about the stock market, the upper quintile represents around 35% considering the finer measure of information. This variable increases to 40% if one considers the broader measure. In my analysis I use the latter, but results remain if I consider the finer one.

As a robustness check, I construct a second proxy of information using the PSID. This variable identifies individuals who report trading activity in the stocks' portion of their portfolio between surveys[13]. In the quantitative section of this article, I present a simple static model that highlights two observations. First, there is a positive relationship between the wealth of the individual and how informed she is. Second, the model predicts that better-informed investors will adjust the portfolio's share of risk assets more aggressively. Using these remarks, I suggest that an individual is better-informed when she belongs to the top 20% (assuming the top 10% renders similar results) and she declares trading activity in the stock part of their portfolio between consecutive surveys. The investor may conduct this trading activity directly or indirectly - if the investor uses financial institutions such as mutual and hedge funds or other financial counseling services. The critical point is that the investor is involved in the decision of portfolio reallocation.

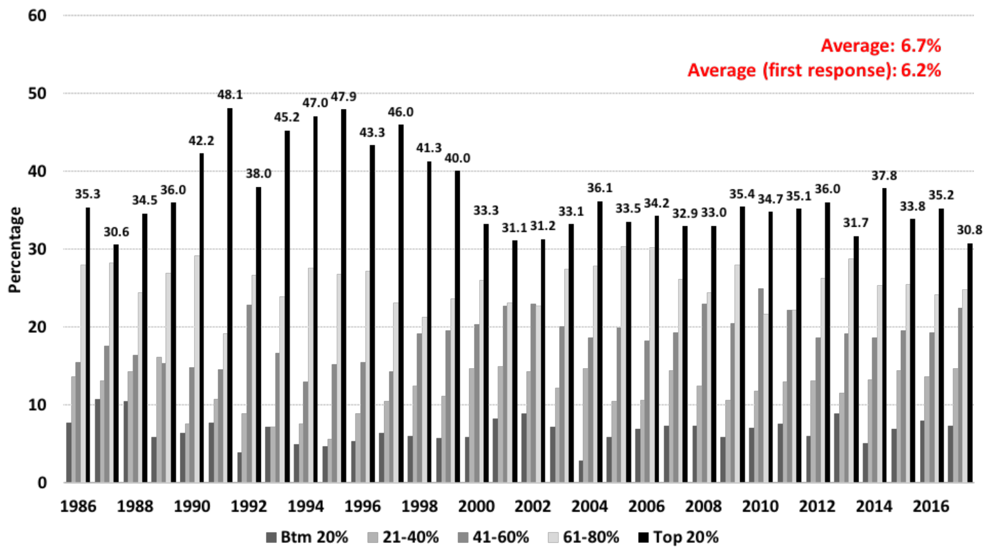
In Appendix A, I provide further justification for the construction of this variable. In addition, I replicate all the results presented in this section using this measure of information and I show that one obtains similar implications[14].

Financial uncertainty shocks. I use the measure of financial uncertainty shocks provided

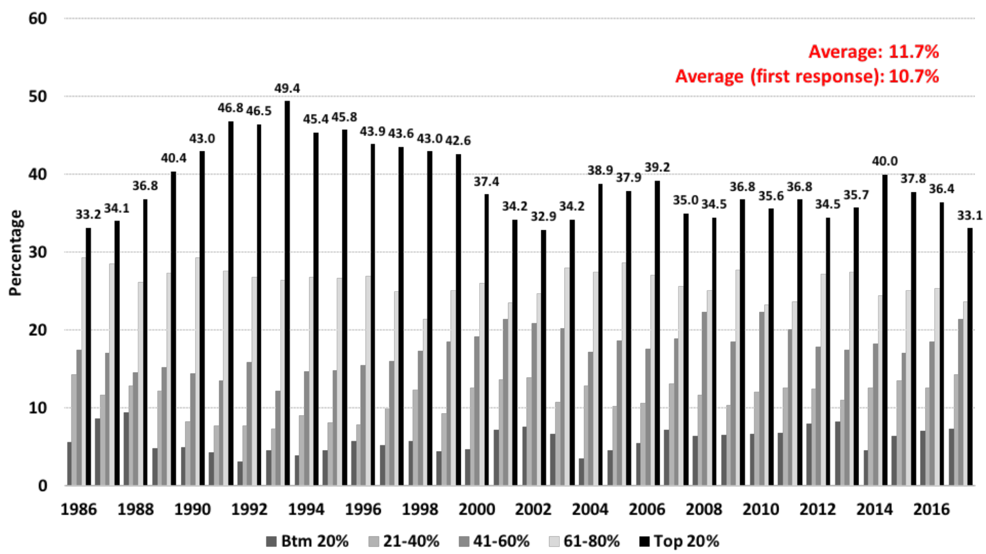
[13]The question is: *Since the previous survey, did [you/you or anyone in your family living there/they] buy or sell any shares of stock in publicly held corporations, stock mutual funds, or investment trusts, including any automatic reinvestments?* The respondents may answer yes bought, yes sold, yes both, or no.

[14]The results in this section are closely related to Chien and Lustig (2010) and Chien, Cole, and Lustig (2012).

Figure 1: **Share of individual by income quintiles among those considered informed**



(a) Finer measure: stock market news

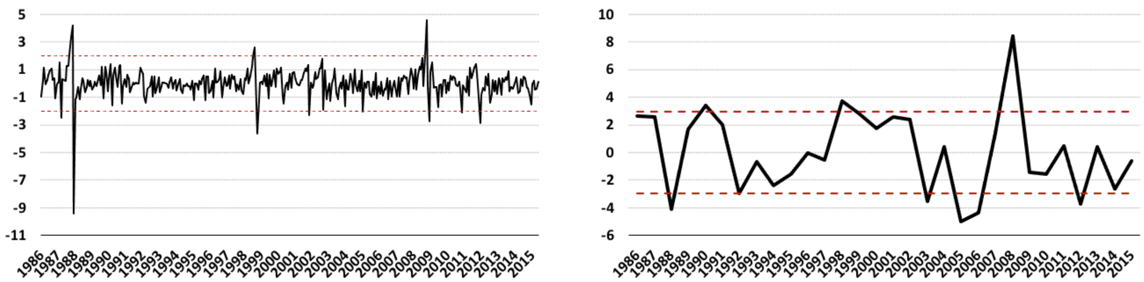


(b) Broader measure: stock market, interest rates, and profits news

Notes: Measures of information. Panel (a) presents the distribution by income quintiles of individuals who heard news about stock market (codes: 36 and 76). Panel (b) presents the same variables but using a broader definition of information including interest rate and profits news (codes: 33, 35, 36, 73, 74, and 76). The first response considers only the first survey for each individual. Source: Michigan Survey of Consumers. The sample spans the period 1986-2017.

by Ludvigson, Ma, and Ng (forthcoming). Specifically, they construct statistical uncertainty indices using the methodology of Jurado, Ludvigson, and Ng (2015). This measure is defined as the volatility of the unforecastable component of the future value of a number of financial variables, conditional on the information set at period t. Appendix C discusses with more detail how this measure is constructed. Figure 2 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.

Figure 2: **Financial uncertainty shocks**



(a) Monthly uncertainty shock (b) Annual uncertainty shock

Notes: The figure shows results from the identified VAR in Ludvigson, Ma, and Ng (forthcoming). Panel (a) reports the structural shock for one particular solution refered to as maxG solution. Panel (b) shows the annual version of the shock. The sample spans the period 1986:01 to 2015:12.

Definition of returns. I use the definition of returns in Fagereng, Guiso, Malacrino, and Pistaferri (2020), who apply 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 for both flows and stocks of the particular asset class. The return to net worth, which is the key concept in the analysis I present below, is

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

where y_{it}^{fin} is the financial income, which includes income from checking, savings, and bonds (CSB) and public equity, y_{it}^{nof} the non-financial income, which includes income from housing and private business, and y_{it}^{debt} are debt payments. W_{it}^{gross} is the gross wealth of agent i at the beginning of period t. $F_{it}^{k} = \Delta W_{it+1}^{k} - \tilde{y}_{it}^{k}$ 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 beginning and end-of-period period wealth minus the income that is capitalized into end-of-period wealth where $\tilde{y}^k_{it}$ is specific to the asset type, with $k \in \{sto, csb, hou\}$; and, F^{gross} is the sum of F^k for all the asset classes. I impose some selection requirements to reduce outliers in the estimation of returns to net worth. In particular, I focus on individuals between 20 and 75 years old. Furthermore, 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 1.0%. To compute returns to net worth, one needs 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 rely on linear interpolation of log wealth components to obtain wealth measures for missing years. I conduct a finer approach in which I take into account the price dynamics of each asset class in the portfolio and obtain similar results.

In the theoretical section of the paper, I present a dynamic model in which agents can invest in bonds (risk-free asset) and in capital (risky asset). To make the comparision between the model and the empirical section as transparent as possible, I also provide results using returns to financial wealth which are computed using the following formula

$$r^{fin}_{it} = \frac{y^{fin}_{it}}{W^{\text{fin}}_{it} + 0.5 * F^{\text{fin}}_{it}} \tag{2}$$

where F^{fin} adds F^k for CSB and stocks. Hence, in the theoretical section, I relate the model results to those pertaining to financial wealth. In this sense, the empirical section presents results on returns to net worth where the assumption is that investors take into account the sources of risk from all asset categories when deciding the allocation of portfolio. Then, I present results on returns to financial wealth to have a direct connection between the model and the empirical facts I propose.

Table 1 presents returns for different asset categories. The average return to net worth, at the individual level, during the sample period (1986 - 2007) was 2.0%, and its standard deviation was 19%. In the case of financial wealth, the average return was 6.0%, and its dispersion 14%. As expected, the dispersion of stocks is higher while the dispersion on checking, savings, and bonds is around 3%, highlighting its role as the risk-free asset. Non-financial wealth return was 9%, with a dispersion of 28%. 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. Some of these observations were already mentioned in the literature for the United States and other countries[15].

Table 1: **Returns for different asset categories**

Wealth Component	Mean	St. Dev.	P10	Median	P90
Net worth	0.02	0.19	-0.15	0.02	0.21
Financial wealth	0.06	0.14	-0.12	0.04	0.21
CSB	0.01	0.03	0.00	0.00	0.05
Stocks	0.11	0.28	-0.26	0.11	0.43
Non-financial wealth	0.09	0.28	-0.17	0.08	0.38
Housing	0.08	0.20	-0.08	0.06	0.26
Private business	0.13	0.44	-0.33	0.07	0.76

Notes: Statistics for the estimated returns for different asset categories for the pooled dataset. CSB refers to checkings, savings, and bonds. See Appendix C for a definition of each asset category. The sample spans the period 1986 - 2017.

Table 2 presents the portfolio composition across the distribution of net worth. The table presents evidence that the portfolio of the bottom 50% is concentrated in private residences and safe assets (checking, saving accounts, and bonds). Moreover, these individuals are highly leveraged. As individuals move toward the upper part of the net worth distribution, stocks and private equity become more 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. As Table A.6 shows, around 60% of individuals in the PSID own a house. However, if one only considers individuals not owing a house, the fact that wealthier individuals hold higher positions in riskier

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

assets remains. Table A.5 in Appendix C presents the portfolio composition of homeowners and renters.

Table 2: **Portfolio composition (all households in the sample)**

	Gross wealth shares				Leverage ratio mort.	Log gross wealth
	Financial wealth		Non-financial wealth			
	CSB	Stocks	Housing	Pri. Bus.		
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

Notes: PSID implied portfolio composition for the pooled dataset. Households are sorted by net wealth. See Appendix C for a definition of each asset category. The sample spans the period 1986 - 2017.

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 advantages which allow 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 while 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 roughly equivalent in the PSID and the SCF.

2.2 Empirical results

In this section, I study the effect of information disparities on returns to net worth and financial wealth. Information is captured by the exposure to news related to the stock market, credit, and profits. The first subsection presents cross-sectional facts that highlight the role of information advantages as a source of return outperformance. Then I propose dynamic facts that show how informed individuals perform better after adverse economic shocks. Appendix A provides the results using my second measure of information.

Cross-sectional results. The first cross-sectional fact asserts that wealthy individuals earn higher returns even after controlling for individual risk in their portfolio. The upper left-hand panel of Figure 3 shows the cross-sectional average and median returns to net worth for agents in different percentiles of the wealth distribution for the period 1986 - 2017. The figure suggests a positive relationship between returns and net worth[16]. One possible explanation for this positive relationship is that wealthy investors adjust their portfolios towards riskier assets. Therefore, a more accurate measure of profitability in investment decisions should take into account the individual risk that investors face. Panel (b) of Figure 3 presents a measure of Sharpe ratio constructed using the following formula

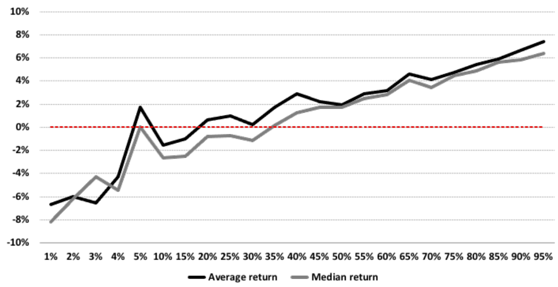
$$SR_{perc} = \frac{\sum_{i=1}^{N_{perc}} \omega_i \left(r_i^{nw} - r_i^f \right)}{\sqrt{\frac{\sum_{i=1}^{N_{perc}} \omega_i \left(r_i^{nw} - r_i^f \right)^2}{\left(\frac{M-1}{M} \right) \sum_{i=1}^{N_{perc}} \omega_i}}}$$

where r_i^f is the average risk-free rate (three-month treasury bill rate) for the investor's investment horizon, ω_i is the wealth weight of each individual in the percentile, and M is the number of nonzero weights. As the Panel shows, there is a positive relationship between the Sharpe ratio and the net worth. This suggests that even when adjusting for the individual portfolio risk, a wealthier individual obtain higher returns. The lower panel of Figure 3 presents the returns and Sharpe ratios for financial wealth. The figure shows a similar positive relationship between returns and the position on the net worth distribution. In addition, Sharpe ratios are also positive sloped suggesting that investors earn higher returns even after controlling for individual risk in their portfolio.

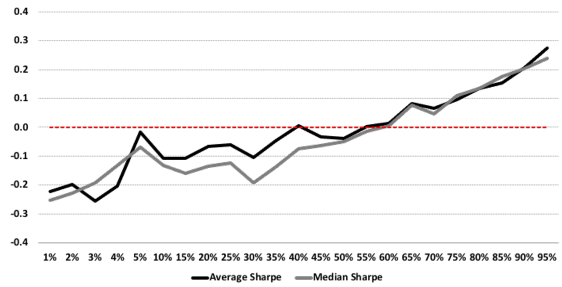
One potential explanation of differences in returns is the existence of heterogeneous risk aversion among investors. For instance, Kekre and Lenel (2020) present a model in which difference in risk aversion is a key ingredient in explaining differences in portfolio choice and returns. In an economy where all assets are priced correctly, one would expect

[16] This observation is relevant since Benhabib, Bisin, and Luo (2019) argues that this positive correlation is important to match the thick upper tail of the wealth distribution.

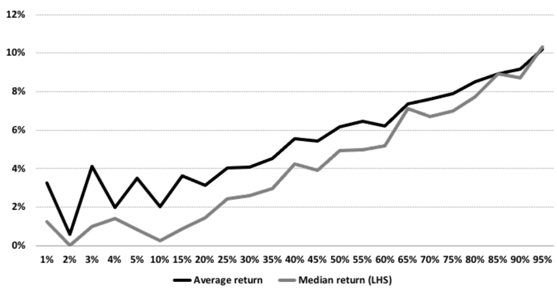
Figure 3: **Returns to net worth and Sharpe ratios along the wealth distribution**



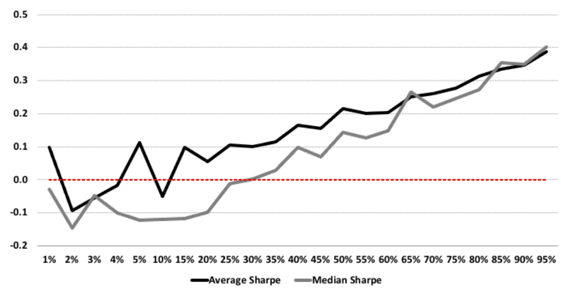
(a) Average and median returns to net worth



(b) Sharpe ratios of returns to net worth



(c) Average and median returns to financial wealth



(d) Sharpe ratios of returns to financial wealth

Notes: Panel (a) presents returns to net worth across the net wealth distribution. For each individual, compute the average, median, and standard deviation of returns. Then, the return for each net-wealth percentile is the weighted average, median, and standard deviation across the individuals in each percentile. The black line reports the cross-sectional average and the gray line the cross-sectional median. Panel (b) presents the Sharpe ratio of returns to net worth. The black line reports the average Sharpe ratios and the gray line the median ones. Panel (c) reports the average and median returns to financial wealth. The black line reports the cross-sectional average and the gray line the cross-sectional median. Panel (d) reports the average and median Sharpe ratios to financial wealth. The sample spans the period 1986 - 2017.

that differences in risk aversion will not cause significant differences in Sharpe ratios along the wealth distribution. Hence, the positive relationship between Sharpe ratios and wealth points toward other factors in explaining differences in returns[17].

The second set of cross-sectional results studies the role of information disparities in a

[17] A more formal approach to rule out risk aversion as a potential explanation returns' heterogeneity is to propose a factor model for the returns to net worth (or financial wealth) and show that wealthy individuals earn a positive alpha while poor investors earn a negative one. This is a future extension in the empirical section presented in this paper.

formal empirical model given by

$$r_{it}^{j} = X_{it}'\beta + \delta \cdot \text{Information}_{it} + u_{it} \tag{3}$$

where r_{it}^{j} is the return of asset category $j = \{\text{nw, fin}\}$ of individual i in period t. Information_{it} is a dichotomous variable constructed using data from SOC. This variable identifies an individual who is exposed to news about financial markets. X_{it} is a vector of covariates with two sets of variables. The first set includes demographic variables such as age, education, gender, and race. The second one comprises portfolio characteristics such as shares on CBS, stocks, housing, private business, and debt. These variables are included to model the observable risk exposure. To avoid potential endogeneity problems, I use beginning-of-period shares. In addition, I include the S&P 500 to control for average market return and the VOX to account for aggregate risk. The last set of variables includes time and state effects.

Table 3 presents the regression results on returns to net worth. Columns (1) - (2) report the additional return to net-worth that an informed individual gets. Results in the first two columns suggest that better-informed individuals outperform in around 1.0%. Unlike the first column, the second one includes controls such as demographics and time and state fixed effects. The third column adds the interaction between the measure of information and the financial uncertainty shock. These numbers show that a better-informed individual earns an additional 0.5% when a negative shock hits the economy. In this paper, I argue that a potential explanation for better-informed investors' outperformance in the wake of adverse economic shocks is a market-timing strategy. Under this strategy, better-informed investors adjust their portfolios when receiving more accurate news about the economy's future path.

Better-information per se is not essential if the investor does not use this advantage. The last column of Table 3 reports the combined effect of exposure to news and declared adjustment activity in the stock part of the portfolio obtained from the PSID. This column highlights better-informed agents who report trading activity earn higher returns. Moreover, the significance of information is lower when including this interaction. This result points toward the potential role of market-timing when investors face adverse economic shocks. These facts are in line with the ones obtained using the second proxy of information I constructed. In particular, this measure combines the declared adjustment activity in the stock part of the portfolio with the wealth distribution position. The results suggest that wealthy individuals who report trading activity outperform wealthy individuals who do not trade and individuals in the bottom 80% of the wealth distribution. A broader discussion of these results is in Appendix A.

Table 3: **Regression results: returns to net worth - Information**

Variables	(1)	(2)	(3)	(4)
Information	0.010***	0.011***	0.011***	0.007*
	(0.004)	(0.004)	(0.005)	(0.005)
Info. # Fin. Unc. Shock			0.005**	
			(0.003)	
Active trading				0.003
				(0.004)
Info. # Active trading				0.017***
				(0.003)
Portfolio shares (beginning of period)	Y	Y	Y	Y
Market Return & VXO	Y	Y	Y	Y
Demographics (age, sex, race)	N	Y	Y	Y
Year and state effects	N	Y	Y	Y
R^2	0.13	0.15	0.15	0.15
Observations	34,116	34,116	34,116	34,116
Number of individuals	3,100	3,100	3,100	3,100

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

Table 4 provides the same analysis considering returns to financial wealth. Note that the coefficients in these regressions are higher since the value of information about the stock market is more important for this asset category. Also, the interaction between information and declared trading activity in the stock part of the portfolio is more relevant in this context since financial wealth includes both CSB and stocks.

At least two other potential mechanisms can explain the outperformance obtained by having better information. First, as the literacy literature[18] suggests, well-educated investors perform better. The results in tables A.3 and A.4 do not support an important role for education. A second channel takes into account the position in the wealth distribution.

[18]See, for instance, Van Rooij, Lusardi, and Alessie (2011) and Van Rooij, Lusardi, and Alessie (2012).

Table 4: **Regression results: returns to financial wealth - Information**

Variables	(1)	(2)	(3)	(4)
Information	0.023***	0.022***	0.021***	0.010*
	(0.004)	(0.004)	(0.004)	(0.008)
Info. # Fin. Unc. Shock			0.006***	
			(0.001)	
Active trading				0.007
				(0.008)
Info. # Active trading				0.019***
				(0.003)
Portfolio shares (beginning of period)	Y	Y	Y	Y
Market Return & VXO	Y	Y	Y	Y
Demographics (age, sex, race)	N	Y	Y	Y
Year and state effects	N	Y	Y	Y
R^2	0.11	0.14	0.15	0.15
Observations	32,745	32,745	32,745	32,745
Number of individuals	3,094	3,094	3,094	3,094

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

Wealthier individuals choose to be better-informed and can perform better. The results in these tables suggest a role for this mechanism; however, this channel's magnitude is lower than the one suggesting a market-timing strategy.

The results discussed above highlight the interdependence between better information about the stock market and stock holdings. Data from the SOC show that within informed individuals, more than 50% hold stocks. In this sense, two forces are mutually dependent and reinforce each other. First, people with public equity decide to be informed about the stock market. Second, better information causes investors' stock holdings. Van Nieuwerburgh and Veldkamp (2010) highlight this double dependence.

In essence, these results suggest that better-informed investors earn around 1.0-2.2% higher returns. Moreover, the empirical models suggest that these investors can hedge better against adverse economic shocks, making around 0.5-0.6% higher returns compared to worse-informed investors. Finally, the interaction of the proxy for information and the declared trading activity points toward a role for a market-timing strategy that I next study in a dynamic setting.

Dynamic results. The preceding section discussed cross-sectional facts on returns to net worth and financial wealth. In this section, I study the dynamic patterns of returns. Panel (a) of Figure 4 presents the cross-sectional average and dispersion of returns to net worth over the sample period. The asset pricing literature highlights that recessions increase the volatility of returns while decreasing their average value[19]. 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 recessions and remains high even after the recession ceases. These two observations highlight that aggregate economic shocks affect the investment opportunities of agents differently along the distribution. Panel (b) and (c) present the measure of financial uncertainty shocks from Ludvigson, Ma, and Ng (forthcoming). Note that uncertainty has a negative correlation with cross-sectional average returns to net worth and financial wealth. This observation suggests that during periods of high financial volatility investors perform worse. In this study, I argue that information disparities, in an environment of noisy private signals, partially explain these facts. In addition, I show that negative economic shocks affect investors differently; and that better-informed investors outperform worse-informed agents when facing adverse shocks.

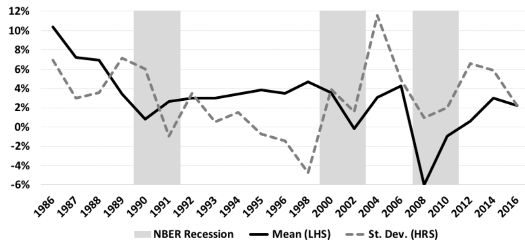
In order to analyze the dynamic response of information differences on returns to net worth and financial wealth, I estimate a forecasting model following Jordà (2005) local projection method. Specifically, the empirical model is given by

$$r_{t+h} = \alpha_h + X_{it}'\beta_h + \delta_h \text{ Information}_{it} + \gamma_h \left(\mathrm{e}_t^F \# \text{ Information}_{it}\right) + u_{it+h} \tag{4}$$

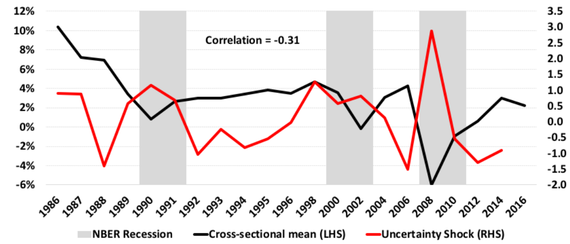
for $h > 1$. e_t^F is Ludvigson, Ma, and Ng (forthcoming) financial uncertainty shock and X_{it} contains the set of controls discussed in the previous section. Figure 5 presents the results. Panel (a) describes an unconditional regression which only includes the information variable (Information_{it}) and inspect how much of the dynamic outperformance is attributed to information advantages. The figure shows that an informed investor can sustain around 0.7% higher returns for four periods. Given the frequency of the PSID, a period in the

[19] See, for instance, Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016).

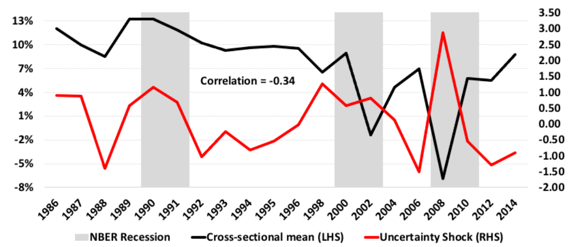
Figure 4: **Net worth returns, the business cycle, and uncertainty**



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



(b) Cross-sectional average return to net worth and uncertainty



(c) Cross-sectional average return to financial wealth and uncertainty

Notes: Panel (a) presents the cross-sectional average return and cross-sectional returns' dispersion over time. Gray bars identify the NBER recession dates. Panel (b) presents the cross-sectional average return and the measure of uncertainty used in the empirical section of the paper. Panel (c) presents the cross-sectional average return to financial wealth. The sample spans the period 1986 - 2015.

analysis covers two years. Panel (b) presents a conditional result which is captured by the coefficient γ_h in (3). This coefficient shows the interaction between the information variable and the financial uncertainty shock. The empirical model suggests that an informed investor can sustain around 0.15% higher returns, compared to worse-informed investors, after an adverse economic shock hits the economy. Panels (c) and (d) present the results on returns to financial wealth. Since the information variable is constructed using the declared exposure to news about stock market, the effect of this variable on returns to financial wealth is higher. The unconditional result suggests that better-informed investors earn 1.0% higher returns for four periods, and, when an adverse economic shock hits the economy, they can achieve around 0.3% higher returns. Then, I follow the suggestive evidence on trading activity discussed in the previos section. I estimate a model similar to that in equation (4) but with the share of stocks out of financial wealth as the left-hand side variable. The results of this regression are in Panel (e)-(f). The results suggest that after an unexpected financial uncertainty shock, better-informed individuals increase the share in stocks and then reduce it once stock prices start to recover. This behavior is consistent with the market-timing strategy. When having information about a future adverse shock, informed investors increase the share of their financial wealth invested in stocks and then reduce it in subsequent periods once stock prices start to recover.

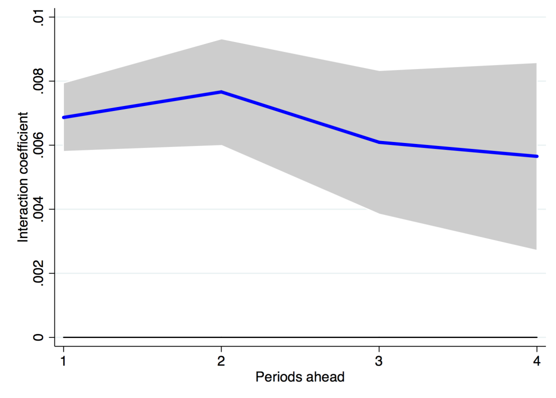
To better distinguish the market-timing strategy and given the fact that individuals in the upper and lower part of the distribution have very different macro-portfolios, I complement the analysis by looking at wealthy individuals (the ones who belongs to the top 20% of the wealth distribution). I then construct a variable that identifies, among these wealthy investors, the ones who are considered informed and who declared adjustments in the stock part of their portfolio. I estimate an unconditional regression, not including the interaction with the financial uncertainty shock, to see if it is indeed the interaction that explains the outperformance. Figure 6 presents the results. Trading activity by informed individuals is able to explain the outperformance in returns to net worth and financial wealth as Panels (a) and (c) show. In the case of the conditional analysis, the results also suggest that market-timing is a potential explanation for the outperformance in returns, see Panels (b) and (d).

To summarize, this section studies the persistent outperformance attributed to better-information. Using a dynamic empirical model, I show that better-informed individuals persistently outperformed worse-informed ones regarding returns to net worth and financial wealth. Moreover, I present evidence that market-timing is a potential explanation for these facts. I reinforce this conclusion by considering only wealthy individuals with similar portfolios, not as exposed to real estate assets as the bottom 80% of the distribution portfolios.

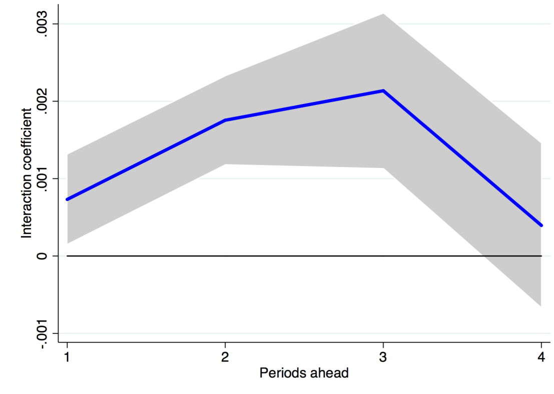
3. Quantitative Analysis

I start this section by presenting a simple static model that links information advantages with initial wealth. The model can qualitatively explain the cross-sectional facts presented in the empirical section. Also, the model suggests that wealthier individuals acquire more

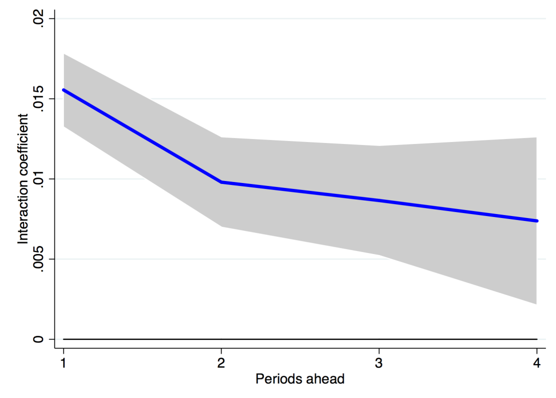
Figure 5: **Impulse-response functions for the informed individuals**



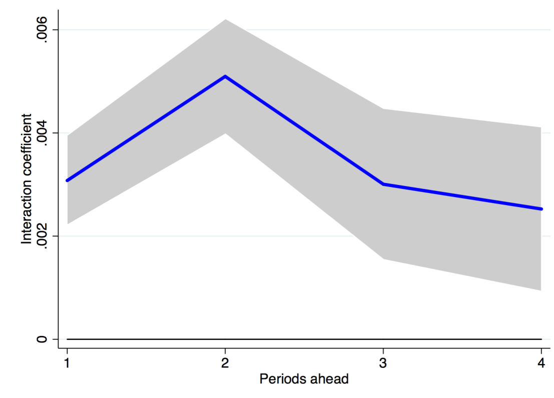
(a) Net-worth: unconditional regression



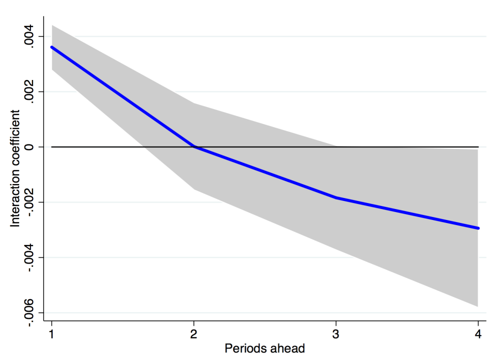
(b) Net-worth: conditional regression



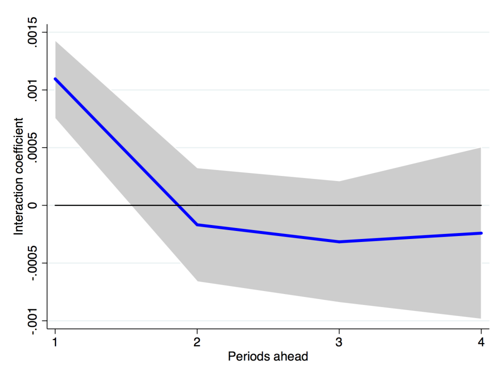
(c) Financial: unconditional regression



(d) Financial: conditional regression



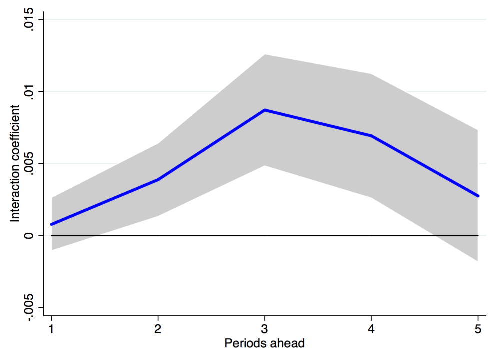
(e) Stock share: unconditional regression



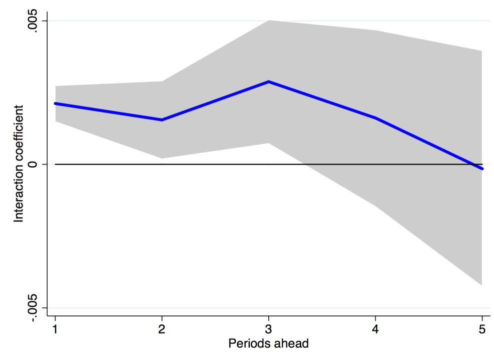
(f) Stock share: conditional regression

Notes: The figure presents the coefficient γ_h for the $h > 1$ local projection regressions in (4). The upper panel presents the results for the returns to net worth. The middle panel reports the results for the returns to financial wealth. The lower panel presents the results considering stocks' share on financial wealth as dependent variable. The left-hand side figures only include the information variable. The right-hand side figures reports the results for the coefficient on the interaction between the information variable and the financial uncertainty shock. Gray areas are the 90% confidence bands.

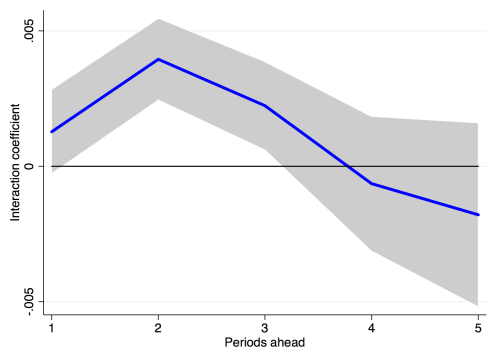
Figure 6: **Market-timing: wealthy individuals**



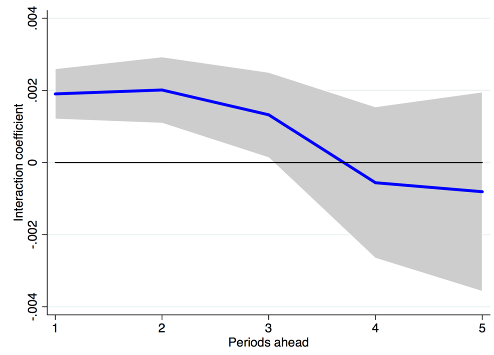
(a) Net-worth: unconditional regression



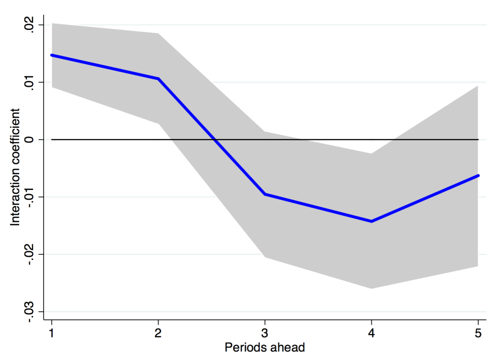
(b) Net-worth: conditional regression



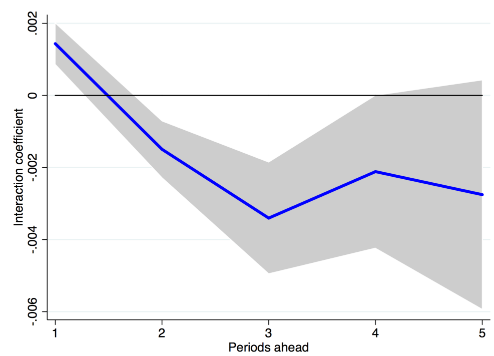
(c) Financial: unconditional regression



(d) Financial: conditional regression



(e) Stock share: unconditional regression



(f) Stock share: conditional regression

Notes: The figure presents the coefficient γ_h for the $h > 1$ local projection regressions in (A.1). The upper panel presents the results for the returns to net worth. The middle panel presents the results for the returns to financial wealth. The lower panel presents the results considering stocks' share on financial wealth as a dependent variable. The left-hand side figures report the active trading variable by informed individuals and the covariates without including the interaction with the financial uncertainty shock. The right-hand side figures report the interaction coefficient. The set of covariates includes demographics (excluding education), beginning-of-period portfolio shares, S&P 500 return, VOX volatility index, and state and time fixed-effects. Gray areas are the 90% confidence bands.

information and tilt their portfolios toward the risky asset. I use these two insights in a dynamic model. I investigate the quantitative implications of uncertainty shocks in a model with dispersed information. 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). There are 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 both sets of agents into two representative households. These households trade in the stock market and in debt markets and differ in the quality of the private information they receive about the economy's fundamental shocks.

Relating the empirical results to the model. The empirical section presents cross-sectional and dynamic facts about returns to net worth and financial wealth. The main result of the cross-sectional analysis is that informed investors earn higher returns. For the dynamic results, I propose that informed agents hedge against adverse economic shocks and outperform worse-informed investors. In this section, I show that a model in which the primary mechanism is the differences in private information quality can rationalize a subset of the empirical facts I presented in the previous section. I relate the models outcome with the results using the measure of information from the SOC. Importantly, given that I do not explicitly consider the housing sector in the model, I focus on the empirical results regarding financial wealth.

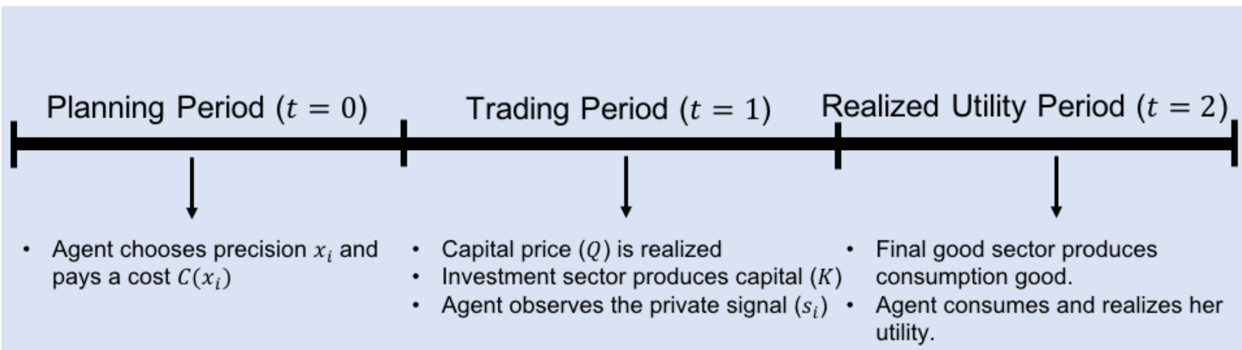
3.1 Insights from a static model

Setup: I build a standard endogenous information acquisition model[20] 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 the capital payoff. There are two types of production sectors,

[20]The model is similar to the ones in Mihet (2019), Peress (2004), and Verrecchia (1982).

an investment good sector which supplies capital, k, subject to quadratic 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 exists at three periods. In the first period (planning period), each agent chooses the private signal precision 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 7 presents the timing of the model.

Figure 7: **Timing in the static 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, which performs instant arbitrage between the price of capital q traded and the number of units of capital in circulation, maximizes profits

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

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

$$k = \kappa \left(q - 1 \right) \tag{5}$$

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 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 discouraging 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 $\theta \sim N(0, \sigma_\theta)$.

Agents i can spend resources acquiring information about the capital payoff η. In practice, the agent pays a variable cost to set the level of the private signal's precision (inverse of the variance). Each investor receives a signal s_i which is an unbiased estimator of the capital payoff; that is, $s_i = \eta + \epsilon_i$ where $\{\epsilon_i\}$ 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, i.e. $x_i^{-1} = \sigma_i$. Agents inccur 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 $U_{0i} = \mathbb{E}_0[U_{0i}(\mathbb{E}_{1i}[u_1(W_1)])]$, defining $U_{1i} = \mathbb{E}_{1i}[u_1(W_1)]$ and $u_1 = \frac{1}{1-\rho}W_1^{1-\rho}$. Agents' objective is to maximize expected utility of terminal wealth W_{1i}.

Solution: The model is solved in two steps. In the first one, corresponding 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, and the precision level. In the second step, corresponding to the planning period, the agent chooses the precision for the private signal x_i. 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 (the capital price 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 the capital 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 (z_{1i}) and shares (α_{1i}) are

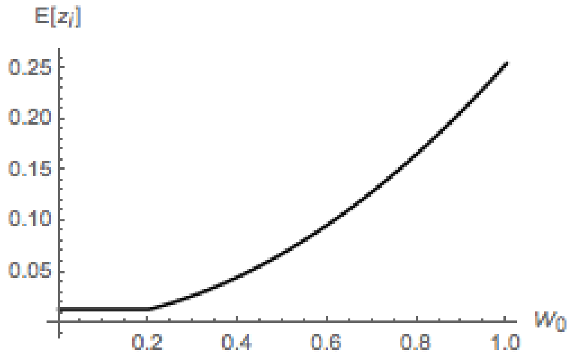
$$\mathbb{E}\left[z_{1i}\right] = \frac{W_{0i}}{\rho}\mathbb{E}\left[\frac{\mathbb{E}_{1i}[\eta] - qR^f}{\mathbb{V}_{1i}[\eta]}\right] \qquad \mathbb{E}\left[\alpha_{1i}\right] = \frac{1}{\rho}\mathbb{E}\left[q\left(\frac{\mathbb{E}_{1i}[\eta] - qR^f}{\mathbb{V}_{1i}[\eta]}\right)\right] \tag{7}$$

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

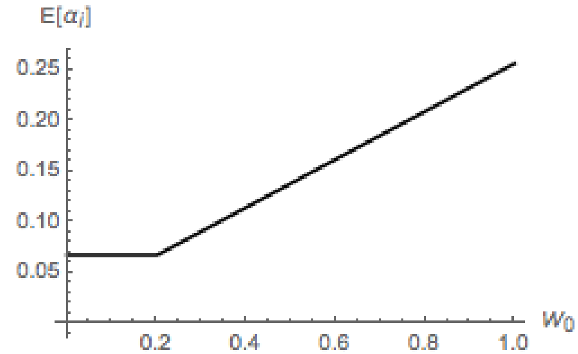
$$\mathbb{E}\left[r_i^n\right] = \mathbb{E}\left[\alpha_{1i}\left(\frac{\eta - q}{q} - r^f\right)\right] + r^f \quad \mathbb{E}\left[SR_i\right] = \frac{\mathbb{E}\left[r_i^n\right] - r^f}{\mathbb{V}\left[r_i^n\right]} \tag{8}$$

Figure 8 presents a graphic representation of the expressions above as a function of the initial wealth. Consistent with the cross-sectional 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 also increases 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. The intuition behind these results rests in the function for information costs. This implies that the cost of information does not scale with the portfolio size while the benefits of acquiring more information do increase with the quantity of information that the agent buys. In other words, the marginal cost of information does not depend on the portfolio size; while the marginal benefit does increase with size. These four graphs suggests that a model with information frictions can rationalize a subset of the empirical facts presented in the previous section.

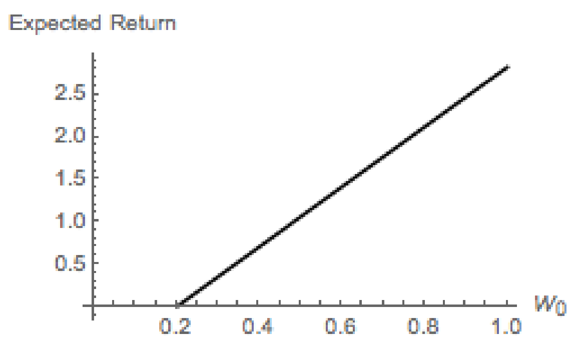
Figure 8: **Static model implications for returns**



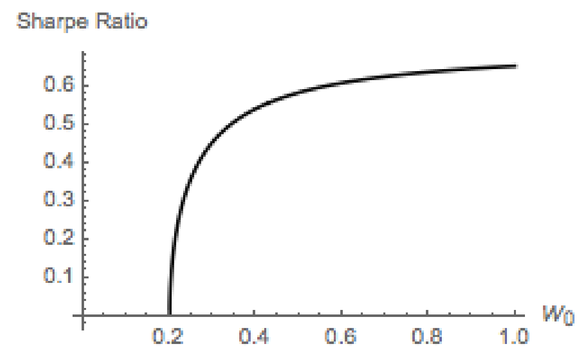
(a) Ex-ante holdings of capital in the portfolio



(b) Ex-ante share in the risky asset



(c) Ex-ante returns to net worth



(d) Ex-ante Sharpe ratio

3.2 Quantitative model

Production sector

Final good sector: The final good firm 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. 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 producer 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

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

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[21]. 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. 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. This sector then pays the revenue as dividends to the households. The dividends per unit of capital are

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

[21] In the stationary version of the model, variables are detrended to ensure a balanced growth path. Then

$$\nu_0 = \frac{1}{1-\xi}\left(\delta + e^{\mu} - 1\right) \qquad \nu_1 = \left(\delta + e^{\mu} - 1\right)^{\frac{1}{\xi}}$$

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 to 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.

For differences in the quality of private information to have a role in the model, I assume that public signals (prices and aggregate quantities) do not reveal all the necessary information that agents need to form expectations. For this reason, following Hassan and Mertens (2017), 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 and the common error shock

$$\mathcal{E}\left[\eta_{t+1}^{k}|S_{jt}\right] = \mathbb{E}\left[\eta_{t+1}^{k}|S_{jt}\right] + \varepsilon_{t}^{k} \qquad k = \{L, S\} \tag{21}$$

where S_{jt} is the state vector and $\varepsilon_t^k \sim N(0, \sigma_{\varepsilon k})$ 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 shocks results in a 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 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. The fact that there is perfect risk sharing among household types allows me to present all the analysis that follows in terms of two representative 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

$$v_{jt}(S_t, k_{jt-1}, b_{jt-1}) = \left((1-\beta)\, \tilde{c}_{jt}^{1-\frac{1}{\psi}} + \beta \mathcal{E}_{jt} \left[\left(v_{jt+1}(S_{t+1}, k_{jt}, b_{jt})\right)^{1-\gamma^j} \right]^{\frac{1-\frac{1}{\psi}}{1-\gamma^j}} \right)^{\frac{1}{1-\frac{1}{\psi}}} \tag{22}$$

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

$$\tilde{c}_{jt} = c_{jt}^{\chi} \left(z_{t-1}\left(1 - l_{jt}\right)\right)^{1-\chi} \tag{23}$$

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

$$\mathrm{ws}_{jt} = \lambda_j \frac{q_{t-1}R_t k_{jt-1} + b_{jt-1}}{q_{t-1}R_t k_{t-1}} \tag{24}$$

where the return on capital holdings R_t is given by

$$R_t = \frac{d_t + (1-\delta)q_t}{q_{t-1}} \tag{25}$$

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

$$c_{jt} + q_t k_{jt} + q_t^f b_{jt} + \Psi_j^b(b_{jt}) = w_t l_{jt} + n_{jt-1} + T_{jt} \tag{26}$$

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 bond holding cost function $\Psi_j^b(b_t^j)$ with[22]

$$\Psi_j^b\left(b_{jt}\right) = q_t^f z_t \frac{\psi_j^b}{2}\left(\frac{b_{jt}}{z_t} - b_{jss}\right)^2 \tag{27}$$

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 both types of 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 (22) subject to (26) 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 good sector's optimal policy, maximizing (14) given the vector of prices.

4. Market's clearing conditions

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

[22] For computational purposes and to rule out the possibility that the better-informed household ends up owning all the wealth, I introduce a quadratic cost function for the worse-informed household. This cost penalizes any deviation of capital stock k_{ut} from a calibrated target k_{uss}.

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 B. 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. Individual 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 B, I show that the model's equation can be expressed as follows

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

The individual state variables $S_{jt} = \{S_t, \mathcal{E}_{jt}[\eta^L_{t+1}], \mathcal{E}_{jt}[\eta^S_{t+1}]\}$ 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^L_t and η^S_t, and the average expectations. I collect this variables into the following vector $S_t = \{k_{t-1}, k_{it-1}, b_{it-1}, \omega_{t-1}, \eta^L_t, \eta^S_t, \{\bar{\mathbb{E}}^L_t\}_{jt}, \{\bar{\mathbb{E}}^S_{jt}\}_j\}$. Furthermore, 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

$$\overline{\mathbb{E}}^k_{jt} = \int \mathcal{E}_{jt}\left[\eta^k_{t+1}\right] dj = \int \mathbb{E}_{jt}\left[\eta^k_{t+1}\right] dj + \varepsilon^k_t \qquad \text{for } k = \{S, L\} \tag{29}$$

where in the second equality, I use the definition of near-rational expectations in equation (21). Proposition B.3 and Assumption 2 present the steps to solve the information part of the model and how information aggregation is achieved.

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; however, I annualize the simulation results when comparing them with the data counterparts. 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 moments, 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 value greater than one is essential to obtain an average risk-free rate with a small standard deviation. 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 value lower than one[23]. However, unlike my model, the 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 informed in the empirical section of this paper. This value comes from the SOC which suggests that 14.5% of the households in the sample declared exposure to financial markets news.

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

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

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)
Measure of better-informed households	λ	14.5%	Share of informed PSID & SOC
		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)

Notes: Externaly set parameters are standard in the literature or can be observed directly from the data.

near-rational 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 (21).

Calibrated parameters: I calibrate the remaining model parameters to target some macro and micro moments. I aim to reproduce some business cycle moments, asset price moments, and portfolio composition presented in the empirical section of the paper. I target six moments which are 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 of per-capita output growth. 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 C presents all the data sources and how these moments are computed. 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).

I calibrate the process for the private signals using data from the SOC. I construct a measure of GDP forecast error using question on this survey. This question asks individuals the following: *About a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?*. Then, I follow Curtin (2019) to construct a point forecast for GDP by running a linear regression of future GDP growth on a balance score (which is the number of positive answers - negative answers over the total plus 100). I run this regression for each group (informed and uninformed) and obtain the average forecast error. Then, I use four moments of these measures to calibrate the four variances needed for the signal process. 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[24]. The value of this ratio is 3.36. The second moment I target is the share of stocks for the worse-informed household[25]. In the data, the value for this variable is 0.40. Table 6 compares the moments in the data to those computed using the model. As the table shows, the model does a good job of replicating the business cycle moments.

Untargeted moments: Table 7 presents the value of some untargeted moments and the empirical counterparts obtained using the data discussed in Appendix C. 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

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

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

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: better-informed household					
Long-run	$\frac{\sigma_{iL}}{\sigma_{\eta L}}$	18.93	$(dy - E_i[dy])^2$	2.2%	2.2%
Short-run	$\frac{\sigma_{iS}}{\sigma_{\eta S}}$	11.06	$(dy - E[dy])^2$	2.5%	2.9%
Private signal precision: worse-informed household					
Long-run	$\frac{\sigma_{uL}}{\sigma_{\eta L}}$	22.71	$(dy - E_u[dy])^2$	2.6%	3.1%
Short-run	$\frac{\sigma_{uL}}{\sigma_{\eta L}}$	13.27	$\frac{(dy-E_i[dy])^2}{(dy-E_j[dy])^2}$	0.85	0.73
		Cross-sectional Moments			
Steady-state Bond Holdings	b_{uss}	8.18	$\frac{\lambda(q_{ss}k_{iss}-b_{iss})}{(1-\lambda)(q_{ss}k_{uss}+b_{uss})}$	3.36	3.30
Steady-state Capital Holdings	k_{uss}	19.95	$\frac{(1-\lambda)q_{ss}k_{uss}}{q_{ss}k_{ss}}$	0.40	0.38

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.

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 good 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 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.

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 reports 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.

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 equation (21) 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 effects of information disparities: In this section, I discuss to what extent differences in information explain the model's results. Recall that agents in the model form expectations using the following formula

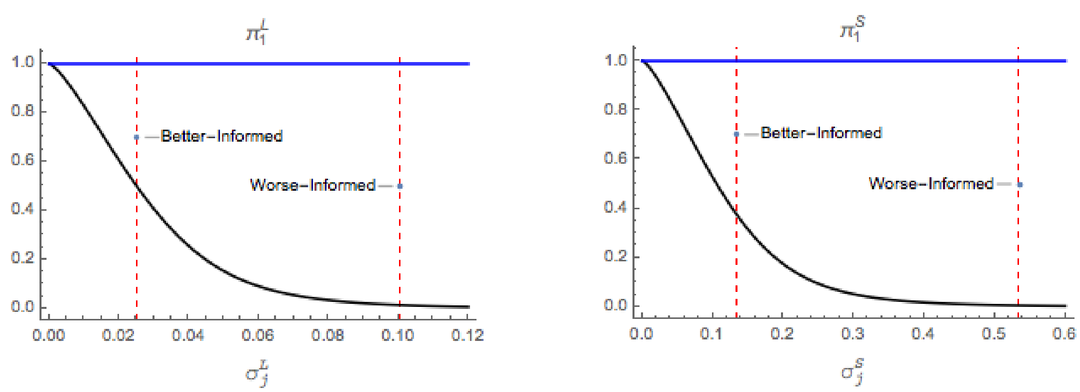
$$\mathcal{E}_{jt}\left[\eta_{t+1}^k\right] = \mathbb{E}_{jt}\left[\eta_{t+1}^k\right] + \varepsilon_t^k$$

where $\mathbb{E}_{jt}\left[\eta_{t+1}^k\right] = \mathbb{E}\left[\eta_{t+1}^k | S_{jt}\right]$ is the conditional expectation of agent j about the next period shock η^k. In Appendix B, equation (B.18) presents the functional form for aggregate expectations of both households types. As the equation shows, the average expectation is a function of next period productivity shock η_{t+1}^k and the near rational shock ε_t; that is

$$\overline{E}_{jt} = \pi_{j0}^k + \pi_{j1}^k \eta_{t+1}^k + \pi_{j2}^k \varepsilon_t^k$$

Agents in the model display a fully rational behavior when the variance of ε_t^k is zero. In this case, the loading coefficient of η_{t+1}^k 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 signals are useless since all information is provided by prices and quantities. When the economy features near-rationality, the loading coefficient is a decreasing function of the private signal variance. Figure 9 presents the coefficient π_{j1}^k 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.

Figure 9: **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.

Cross-sectional facts: Model vs. Data. In this section, I relate the model with the empirical results I presented before. I define individual return to net worth and the share on risky assets as

$$r_{jt+1} = \mathrm{sR}_{jt}\left(r^e_{t+1}\right) + r^f_t$$
$$\mathrm{sR}_{jt} = \frac{q_t k_{jt}}{q_t k_{jt} + b_{jt}}$$

Table 8 presents the simulation results for a set of variables in the model. The first column reports the value of these variables in the data. The second column presents the outcome of the benchmark economy where households display a near-rational behavior and the differences in the precision of the private signal between households matter. The last column presents an economy exactly the same as that of the benchmark, but where differences in information do not play a role. Therefore, by comparing these two economies, the effect of information disparities between households can be measured.

The first panel of Table 8 reports some asset pricing moments. Note that the risk-free rate is higher in the benchmark economy. This is because near-rationality increases risk in the economy since it delays the resolution of uncertainty about future productivity shocks. Then, households engage in precautionary savings to reduce their risk exposure. For the same risk considerations, households require a higher equity premium.

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

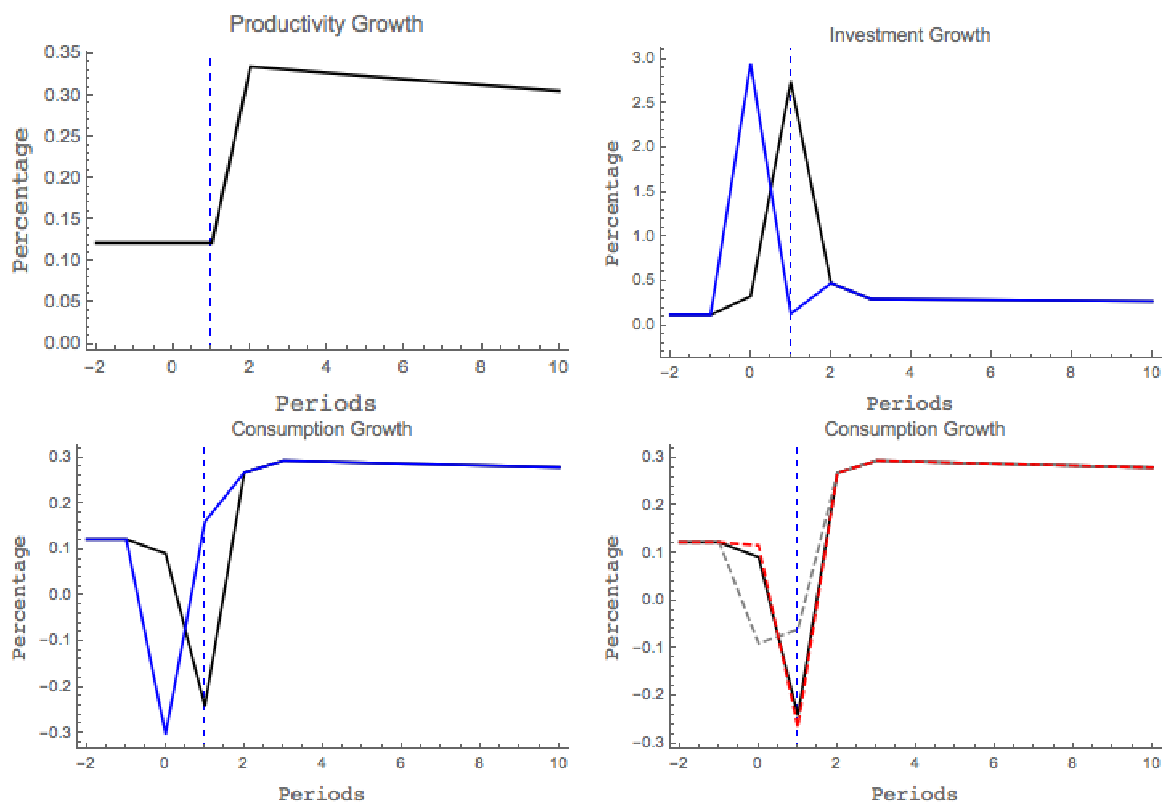
Variable	Data	Benchmark Economy	Rational Economy
		Asset Pricing Moments	
$\mathbb{E}[r^f]$	0.78%	0.79%	1.25%
$\sigma(r^f)$	2.32%	1.15%	1.99%
$\mathbb{E}[r^{Lev}_{ex}]$	4.82%	4.88%	3.94%
$\sigma(r^{Lev}_{ex})$	18.86%	13.28%	12.32%
		Micro Moments	
$\mathbb{E}[(r_i - r_u)]$	2.20%	2.04%	1.36%
$\sigma[r_j]$	1.44%	0.95%	0.60%
$\mathbb{E}[\mathrm{ws}_i]$	54.6%	54.4%	52.0%

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. In the data, the sample spans the period 1948-2015.

The second panel of Table 8 reports the first set of moments that relate the model with the empirical part. First, the model is able to explain the difference in returns to financial wealth observed in the empirical section (see Table 4). In explaining these results, the third column reports the result of an economy subject to the same initial portfolio composition and the same shocks. Hence, the difference in the second and third column is the relevance of information frictions. As the panel suggests, information frictions, and in particular differences in the precision of private signals, bring the model closer to the data. Second, the model falls a bit short in explaining the cross-sectional dispersion of returns. However, it is important to mention that information frictions increase this dispersion in 35 basis points compared to the economy in the third column. Finally, the wealth share of informed individuals is similar to that in the data, and one can see that information frictions result in around 2.4% higher wealth share.

Impulse response functions. Figure 10 presents 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. Therefore, 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 this household's measure is 86%, its effect over the aggregate economy is higher. The lower-left panel shows the same pattern for consumption; under the fully rational economy consumption adjusts 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 the response of aggregate consumption by more.

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



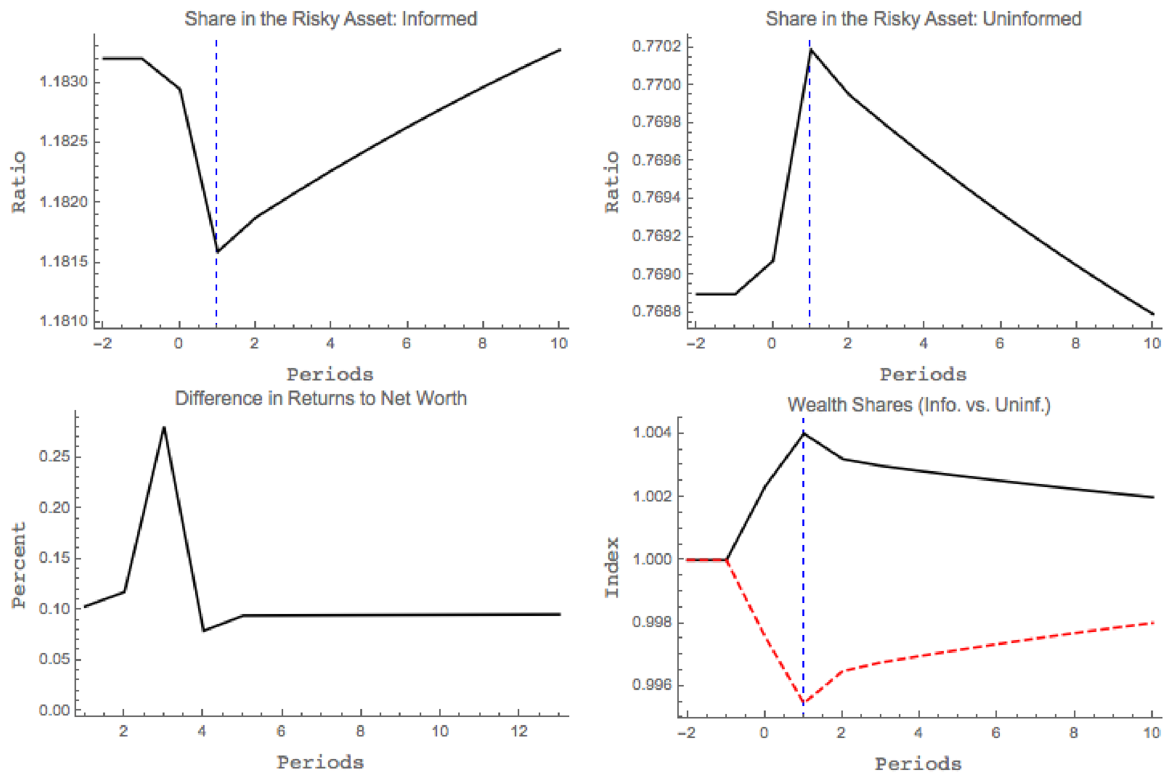
Notes: The figure presents the IRF for a 2 standard deviation shock on η^L that materializes in period 1. The upper-left panel presents the shock. The upper-right panel presents the investment growth rate. The lower-left panel shows the aggregate consumption growth rate and the lower-right panel presents 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.

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 which 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 increase consumption. When the IES is greater than 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.

Figure 11 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 market-timing strategy. This is in line with the empirical evidence I presented above, however in opposite direction because in this case the shock has positive implications. This result 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 outcome 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.

Figure 11: **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.

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 and to present the second set of results that relate the model with the empirical section, I include an aggregate noise component into the households' private signal. 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. I calibrate these processes to obtain the coefficients in the third column of Table 4. Since I need to calibrate two variances, I target the information coefficient and the interaction using the endogenous financial uncertainty shock (discussed below) and an indicator variable that identifies the better-informed household on simulated data from the model. 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.

Following the lead of Bloom (2009), growing literature argues that uncertainty shocks, along with certain types of frictions, are driving forces of business cycles in general equilibrium[26]. 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[27].

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. Using the capital price in the model, I construct an index of financial uncertainty as follows

$$\mathcal{U}_{jt}^{f}(h) \equiv \sqrt{\mathbb{E}\left[\left(q_{t+h} - \mathcal{E}\left[q_{t+h}|S_{jt}\right]\right)^2 |S_{jt}\right]} \tag{31}$$

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

[27]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 S_{jt} is the information set available of household $j = \{i,\, u\}$ at period t. My definition of uncertainty will then aggregate individual uncertainties of both households. 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 21). Let $f_{jt}^q = \left(q_{t+1} - \mathcal{E}\left[q_{t+h}|S_{jt}\right]\right)^2$ be the square forecast error. This is an endogenous object obtained from the model. I then parametrize the outter expectation running the following regression

$$\mathcal{E}\left[f_{jt}^q|S_{jt}\right] = \widehat{F}\left(S_{jt}, \{e_t^k\}_{k=L,S}\right)$$

With a measure of financial uncertainty in hand, I follow Ludvigson, Ma, and Ng (forthcoming) who constructs a measure of 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. In my model, I implicitly assume that the aggregate noise shock in private signals causes households to incur 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

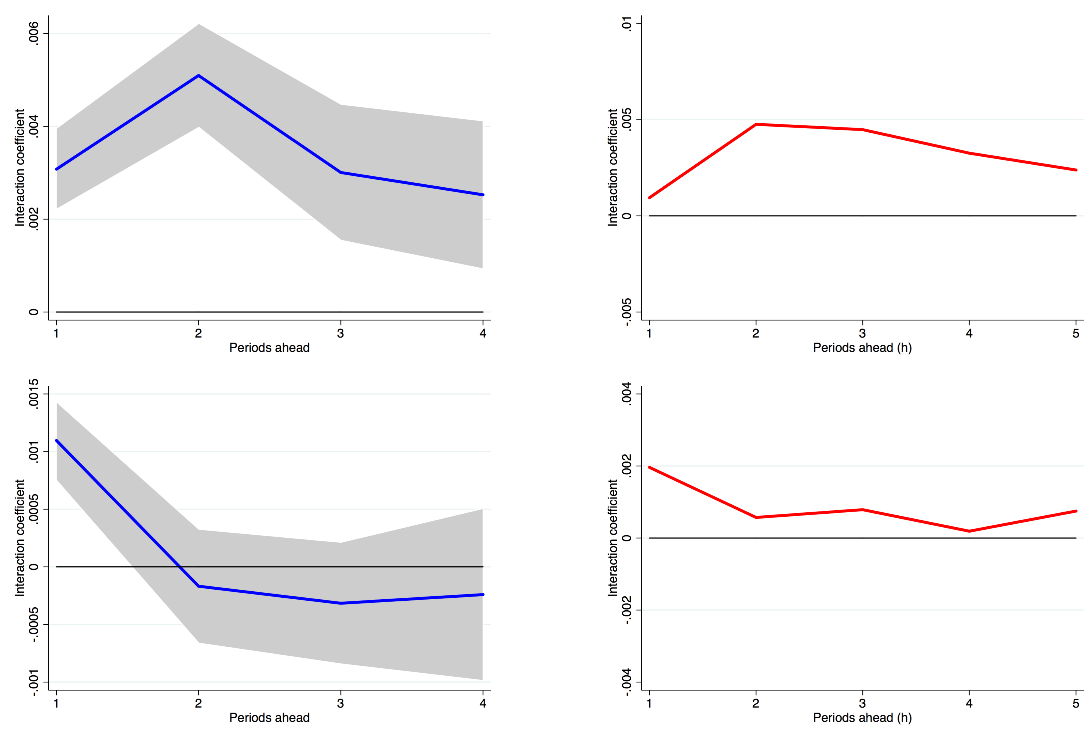
$$\mathcal{U}_{qt}(1) = \beta_0 + \beta_1\omega_t + \beta_2\eta_t^L + \beta_3\eta_t^S + \beta_4\mathcal{U}_{qt-1}(1) + \epsilon_t^F$$

Therefore, the measure of unanticipated financial uncertainty shocks that I will use is $\{\widehat{\epsilon}_t^F\}$. 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 $\{\widehat{\epsilon}_t^F\}$ over return heterogeneity and portfolio allocation

$$x_{jt+h} = \alpha_h + \beta_h I_{jt} + \gamma_h\left(\widehat{\epsilon}_t^F \# I_{jt}\right) + \varepsilon_{t+h}$$

where x_{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. The right-hand panels of Figure 12 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 good job in explaining the effect of uncertainty shocks on returns to net worth across households. Moreover, the model qualitatively produces a decreasing portfolio share on risky asset.

Figure 12: **Data vs. Model: Local Projection Regressions**



Notes: The left-hand side panel present the local projection regressions coefficient of the interaction between uncertainty shocks and the information variable using the PSID/SOC data. The right-hand-side panel presents the local projection regression coefficient γ_h using simulated data. The empirical model is $f_{jt+h} = \alpha_h + \beta_h I_{jt} + \gamma_h \left(\hat{\epsilon}_t^F \# I_{jt}\right) + \varepsilon_{t+h}$ 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.

5. Conclusion

In this paper, I propose a theory that links heterogeneity in returns to information frictions among investors. Using a panel of U.S. households, I first present evidence that returns to net worth correlate positively with wealth. This positive relationship remains when I consider risk-adjusted returns, which implies individual Sharpe ratios positively associated with wealth. I construct a measure of information based on declared exposure to news about financial markets. Using this measure, I establish novel cross-sectional facts that suggest that informed investors earn higher returns.

Then, I establish new dynamic empirical facts that show how better-informed wealthier individuals earn higher returns after a financial uncertainty shock hits the economy through market-timing strategies. To better distinguish this strategy due to the difference in portfolios across the wealth distribution, I consider wealthy individuals. I show that among them, the better-informed investors who declare adjustments in the stock part of their portfolio make higher returns. This result suggests market-timing strategies as a potential contributor to the observed outperformance in returns.

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 economys fundamental shocks; however, the signals precision differs between them. The model does a good job of matching macroeconomic and financial moments in the data. The model also fits important cross-sectional moments, suggesting that information disparities are essential to generate realistic amounts of heterogeneity in returns and produce wealth inequality levels similar to those observed in the data.

Finally, I relate the model with the empirical dynamic facts by constructing a model-based endogenous measure of uncertainty. I show that after a financial uncertainty shock, the better-informed household can sustain higher returns persistently. Furthermore, the model predicts that this household will adjust the portfolios composition by increasing the share in the risky asset when the price has decreased and then decreasing this share as the price recovers, suggesting a market-timing behavior consistent with my empirical results.

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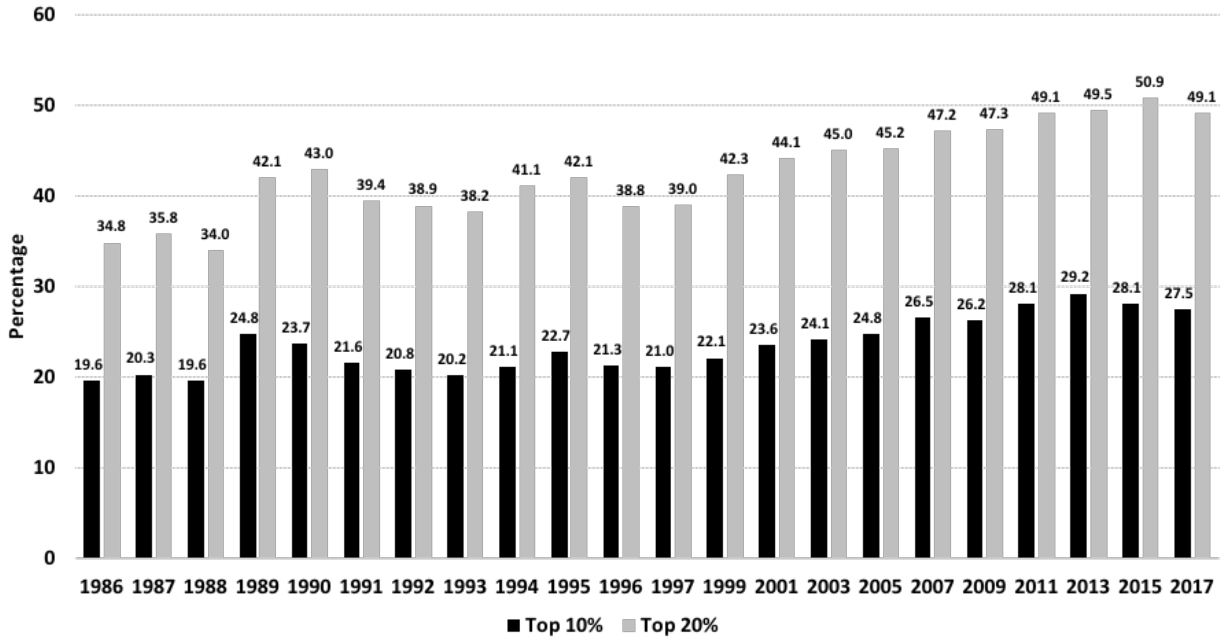
A. Additional results using trading frequency as a proxy of information advantages

Starting with the 1989 wave, the PSID asks respondents several question regarding portfolio rebalances. In particular, I am interested 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?* The respondents may answer yes bought, yes sold, yes both, or no.

This variable identifies individuals who report trading activity in the equity portion of their portfolio between surveys. In the quantitative section of this article, I present a simple static model that highlights two observations. First, there is a positive relationship between the wealth of the individual and the acquisition of information. Second, the model predicts that more informed people will adjust the portfolio's share of risk assets more. Using these remarks, I suggest that an individual is more informed when she belongs to the top 20% (assuming the top 10% renders similar results) and she declares trading activity in the stock part of her portfolio between consecutive surveys. Figure A.1 presents the fraction of respondents in each survey wave that belong to the top 10% and 20% of the wealth distribution. As the figure suggests, wealthier individuals explain almost 50% of the reported trading activity in the PSID.

At least two studies support my choice of trading activity of wealthy individuals as a proxy for information advantages. Gargano and Rossi (2018) use a novel brokerage account data set to construct measures of attention based on the number of minutes that investors spend on brokerage account website, the total number of research pages visited by the investor while in the brokerage account websites, and the number 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 a 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. On the theoretical front, Kacperczyk, Nosal, and Stevens (2019) show that better-informed agents adjust the size and the composition of their

Figure A.1: **Share of wealthy individuals declaring portfolio adjustments**



Notes: The figure presents the share of wealthy individuals who have declared adjustments in their holdings of stocks since the last interview. The black bars report individuals in the top 10% of the wealth distribution and the gray bars report individuals in the top 20% of the wealth distribution. The sample spans the period 1986-2017.

portfolios towards risky assets. So, one can argue that more informed agents will trade more intensively in, for instance, public equity or stocks.

Next, I present the results using my second proxy of information, declared trading activity of top 20% individuals. The first column of Table A.1 suggests that wealthy investors who declared trading activity in the stock part of their portfolio since the last survey earn 3.7% higher returns. This result is robust to the addition of demographic controls, year/state effects, and education, a variable that is likely positively correlated with information advantages. The third colum adds the interaction between this variable and the financial uncertainty shock. In this case, the empirical model suggests that a wealthy investor who declared trading activity earns an additional 0.4% more in the wake of big economic shocks. In the last column I add three additional variables. The first one defines individuals in the top 20% of the distribution that do not adjust the stock part of the portfolio from the previous survey. The second and third variables consider individuals in the bottom 80% of the distribution that did not adjust and that did adjust, respectively. Therefore, these variables give the effect compared to the individuals in the top 20% of the distribution who declared to adjust the stock part of the portfolio. These results suggest that wealthier individuals not trading earn on average -0.8% lower returns with respect to the wealthier individuals who trade. If the individuals belong to the bottom 80%, they earn -3.3% if they do not trade and -4.2% if they adjust. 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 who do not trade as often[28]. Table A.2 provides the same analysis only for returns to financial wealth.

Table A.1: **Regression results: returns to net woth**

Variables	(1)	(2)	(3)	(4)	(5)
Active trading, top 20%	0.037***	0.037***	0.036***	0.035***	
	(0.003)	(0.003)	(0.003)	(0.003)	
Act. trading # Fin. Unc. Shock				0.004***	
				(0.001)	
No active trading, top 20%					-0.008***
					(0.003)
No active trading, btm. 80%					-0.033***
					(0.004)
Active trading, btm. 80%					-0.042***
					(0.004)
Portfolio shares (beginning of period)	Y	Y	Y	Y	Y
Market Return & VXO	Y	Y	Y	Y	Y
Demographics (age, sex, race)	N	Y	Y	Y	Y
Education	N	N	Y	N	N
Year and state effects	N	Y	Y	Y	Y
R^2	0.185	0.201	0.203	0.208	0.212
Observations	65,214	65,214	65,214	61,491	65,214
Number of individuals	9,603	9,603	9,603	9,221	9,603

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

I now present the dynamic analysis using the second measure of information. In this case, the empirical model I estimate is given by

$$r_{t+h} = \alpha_h + X'_{it}\beta_h + \delta_h \text{ trading-top-20\%}_{it} + \gamma_h \left(\mathrm{e}_t^F \# \text{ trading-top-20\%}_{it}\right) + u_{it+h} \qquad \text{(A.1)}$$

where trading-top-20%$_{it}$ is the variable that identifies wealthy individuals that declared trading activity from the previous survey. Figure A.2 shows the estimate of γ_h for $h > 0$, left-hand

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

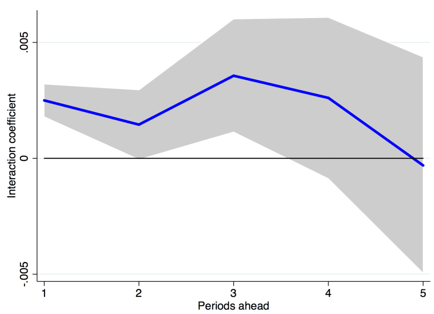
Table A.2: **Regression results: returns to financial wealth**

Variables	(1)	(2)	(3)	(4)	(5)
Active trading, top 20%	0.042***	0.039***	0.039***	0.037***	
	(0.003)	(0.003)	(0.003)	(0.003)	
Act. trading # Fin. Unc. Shock				0.003***	
				(0.001)	
No active trading, top 20%					-0.010***
					(0.003)
No active trading, btm. 80%					-0.034***
					(0.003)
Active trading, btm. 80%					-0.049**
					(0.003)
Portfolio shares (beginning of period)	Y	Y	Y	Y	Y
Market Return & VXO	Y	Y	Y	Y	Y
Demographics (age, sex, race)	N	Y	Y	Y	Y
Education	N	N	Y	N	N
Year and state effects	N	Y	Y	Y	Y
R2	0.185	0.201	0.203	0.208	0.212
Observations	65,214	65,214	65,214	61,491	65,214
Number of individuals	9,603	9,603	9,603	9,221	9,603

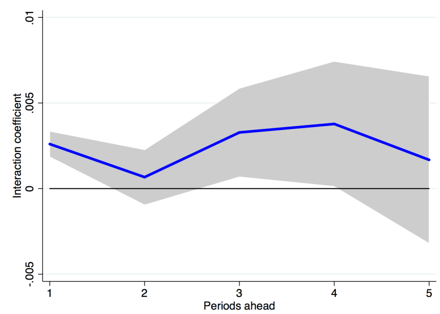
Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The sample spans the period 1986 - 2017.

side panels only include trading-top-20%$_{it}$ as covariate and the right-hand side panels include all the covariates discussed before. Panels (a) and (b) show conditional results suggesting that individuals in the top 20% of the distribution who declared trading activity earn around 0.3% higher return to net worth after a negative economic shock. Panels (c) and (d) present the results considering financial wealth. In this case, an investor considered better-informed can sustain around 0.5 - 0.7% higher returns in the wake of an adverse economic shock. In this section, I argue that a proxy for information advantage is declared trading in stocks. 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. I estimate a model similar to that in equation (A.1) but with the share of stocks out of financial wealth as the left-hand side variable. The results of this regression are in Panel (d)-(e). The results suggest that after a financial uncertainty shock, individuals in the top 20% of the distribution who declared trading activity increase the share in stocks and then reduce it once stock prices start to recover. This behavior suggests a 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 (see the main text for results that reinforce this observation).

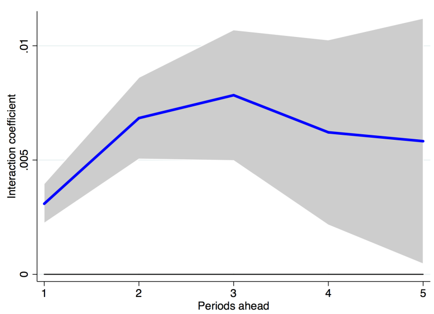
Figure A.2: **Impulse-response functions after a financial uncertainty shock**



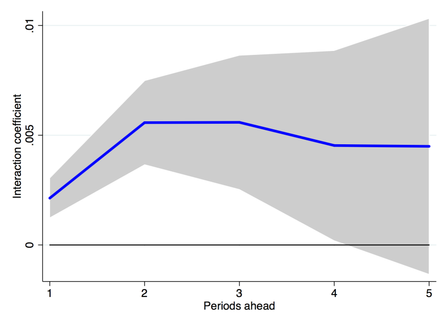
(a) Net-worth: includes active trading$_{it}$ in X'_{it}



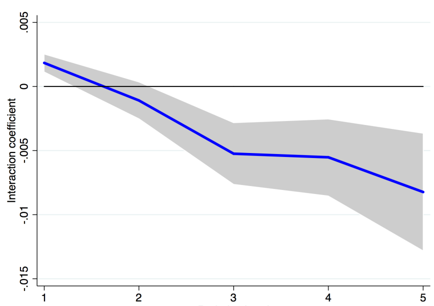
(b) Net-worth: includes all covariates in X'_{it}



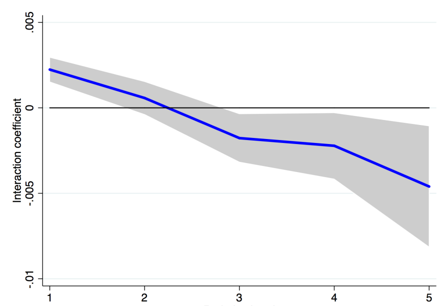
(c) Financial: includes active trading$_{it}$ in X'_{it}



(d) Financial: includes all covariates in X'_{it}



(e) Stock share: includes active trading$_{it}$ in X'_{it}



(d) Stock share: includes all covariates in X'_{it}

Notes: The figure presents the coefficient γ_h for the $h > 1$ local projection regressions in (A.1). The upper panel presents the results for the returns to net worth. The middle panel presents the results for the returns to financial wealth. The lower panel presents the results considering stocks' share on financial wealth as dependent variable. The left-hand side figures only include the active trading variable and the interaction coefficient. The right-side figures add, as covariates, demographics (excluding education), beginning-of-period portfolio shares, S&P 500 return, VOX volatility index, and state and time fixed-effects. Gray areas are the 90% confidence bands.

A.1 Information, education, and wealth

Table A.3 and A.4 add to the analysis of other potential channels through which informational advantages operate. First, I present results for educational attainment. The literacy literature[29] suggests a role for education on net-worth, stock participation, and saving decisions. Then, I report results to analyze the combined effect of information and the wealth distribution position. The static model I present in this paper's quantitative part stresses the positive relationship between information and wealth[30].

The second column of this table presents the results including a variable of education (whether the individual went to high school or college). Note that education is not able to explain the outperformance of returns. When I interact education with information, the coefficient is significative at 10% and explain around 0.2% higher returns. Similarly, Fagereng, Guiso, Holm, and Pistaferri (2020) find a significant positive relationship between education and return to net-worth. However, using an IV for education, this result vanishes. They conclude that general education has no causal effect on individual performance in financial markets.

The last column discusses the role of the position of wealth distribution. Theoretical models of information acquisition point toward the positive relationship between better information and wealth; a wealthier investor will acquire more information and hence will be able to earn higher returns. The results in the table suggest that wealthy informed individuals outperform worse-informed ones in around 0.9%. Moreover, an investor who belongs to the top 20% of the wealth distribution makes 0.6% higher returns.

B. 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.

[29] See, for instance, Van Rooij, Lusardi, and Alessie (2011) and Van Rooij, Lusardi, and Alessie (2012).

[30] Also, Peress (2004) and Kacperczyk, Nosal, and Stevens (2019) stress this positive relationship.

Table A.3: **Regression results: returns to net worth - Information**

Variables	(1)	(2)	(3)
Information	0.011***	0.010***	0.005*
	(0.004)	(0.004)	(0.003)
Education		0.001	
		(0.003)	
Top 20%			0.006*
			(0.004)
Info. # Education		0.002*	
		(0.001)	
Info. # Top 20%			0.009***
			(0.002)
Portfolio shares (beginning of period)	Y	Y	Y
Market Return & VXO	Y	Y	Y
Demographics (age, sex, race)	Y	Y	Y
Year and state effects	Y	Y	Y
R^2	0.15	0.15	0.17
Observations	34,116	34,116	34,116
Number of individuals	3,100	3,100	3,100

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

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

Table A.4: **Regression results: returns to financial wealth - Information**

Variables	(1)	(2)	(3)
Information	0.022***	0.021***	0.007*
	(0.004)	(0.004)	(0.005)
Education		0.005	
		(0.006)	
Top 20%			0.006**
			(0.003)
Info. # Education		0.003*	
		(0.001)	
Info. # Top 20%			0.012***
			(0.006)
Portfolio shares (beginning of period)	Y	Y	Y
Market Return & VXO	Y	Y	Y
Demographics (age, sex, race)	N	Y	Y
Year and state effects	N	Y	Y
R^2	0.14	0.15	0.18
Observations	32,745	32,745	32,745
Number of individuals	3,094	3,094	3,094

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

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 the derivative with respect to bond holdings. Note that the model presents bond adjustment costs. These are necessary to ensure the existence of a well-defined deterministic steady state. The first-order condition is given by

$$\left[\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}\left(-\psi_j^b\left(\frac{b_{jt}}{z_t}-b_{jss}\right)-1\right)q_t^f \right.$$
$$\left.+\beta\left(\mathcal{E}_{jt}\left(v_{jt+1}(b_{jt},k_{jt})\right)^{1-\gamma^j}\right)^{\frac{\gamma^j-1/\psi}{1-\gamma^j}}\mathcal{E}_{jt}\left[\left(v_{jt+1}(b_{jt},k_{jt})\right)^{-\gamma^j}v_{jb,t+1}\right]\right]=0 \tag{B.2}$$

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

$$\left[-\chi(c_{jt})^{-1}(1-\beta)\left((c_{jt})^{\chi}\left(z_{t-1}(1-l_{jt})\right)^{1-\chi}\right)^{1-\frac{1}{\psi}}q_t \right.$$
$$\left.+\beta\left(\mathcal{E}_{jt}\left(v_{jt+1}(b_{jt},k_{jt})\right)^{1-\gamma^j}\right)^{\frac{\gamma^j-1/\psi}{1-\gamma^j}}\mathcal{E}_{jt}\left[\left(v_{jt+1}(b_{jt},k_{jt})\right)^{-\gamma^j}v_{jk,t+1}\right]\right]=0 \tag{B.3}$$

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 envelope 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

$$\mathcal{M}_{j,t,t+1} = \beta \left(\frac{v_{jt+1}}{\left(\mathcal{E}_{jt} \left(v_{jt+1} \right)^{1-\gamma^j} \right)^{\frac{1}{1-\gamma^j}}} \right)^{1/\psi - \gamma^j} \left(\frac{c_{jt+1}}{c_{jt}} \right)^{-1} \left(\frac{(c_{jt+1})^{\chi} \left(z_t (1 - l_{jt+1}) \right)^{1-\chi}}{(c_{jt})^{\chi} \left(z_{t-1} (1 - l_{jt}) \right)^{1-\chi}} \right)^{1-\frac{1}{\psi}} \tag{B.4}$$

Hence, the Euler equations for bonds and capital holdings are

$$1 = \mathcal{E}_{jt} \left[\mathcal{M}_{j,t,t+1} \frac{R_t^f}{1 - \psi_j^b \left(\frac{b_{jt}}{z_t} - b_{jss} \right)} \right] \tag{B.5}$$

$$1 = \mathcal{E}_{jt} \left[\mathcal{M}_{j,t,t+1} R_{t+1} \right] \tag{B.6}$$

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

$$\frac{w_t}{z_{t-1}} = \frac{1-\chi}{\chi} \frac{c_{jt}}{z_{t-1}(1 - l_{jt})} \tag{B.7}$$

Production sector: The production sector consists 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

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

$$r_t^k = \alpha z_t^{1-\alpha} \left(\frac{k_{t-1}}{l_t} \right)^{\alpha - 1} \tag{B.9}$$

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. The investment firm pays 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

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

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

$$\pi_t^x = q_t \left(\Psi'\left(\frac{x_t}{k_{t-1}}\right)\frac{x_t}{k_{t-1}} - \Psi\left(\frac{x_t}{k_{t-1}}\right)\right) \tag{B.11}$$

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) the bond market

$$l_t = \sum_j \lambda^j l_{jt} \tag{B.12a}$$

$$k_t = \sum_j \lambda^j k_{jt} \tag{B.12b}$$

$$k_t = (1-\delta)\, k_{t-1} + x_t + \Psi\left(\frac{x_t}{k_{t-1}}\right) k_{t-1} \tag{B.12c}$$

$$0 = \sum_j \lambda^j b_{jt} \tag{B.12d}$$

B.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 conditions. Then, to make variables stationary I use the following rules

$$\tilde{c}_{jt} \equiv \frac{c_{jt}}{z_{t-1}} \quad \tilde{x}_t \equiv \frac{x_t}{z_{t-1}}, \quad \tilde{w}_t \equiv \frac{w_t}{z_{t-1}}, \quad \tilde{b}_{jt} \equiv \frac{b_{jt}}{z_t}, \quad \tilde{k}_{jt} \equiv \frac{k_{jt}}{z_t}, \quad \tilde{k}_t \equiv \frac{k_t}{z_t},$$
$$\tilde{v}_{jt} \equiv \frac{\frac{v_{jt}}{z_{t-1}}}{\left(\frac{c_{jt}}{z_{t-1}}\right)^{\chi} (1-l_{jt})^{1-\chi}}, \tag{B.13}$$

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 short-term productivity shocks (η_t^L and η_t^S), amd the aggregate expecations for the long and short-term 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

$$f_1(S_{jt}) = \mathcal{E}_{jt}\left[f_2(S_{jt}, S_{jt+1})\right] \tag{B.14}$$

The model equations are

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

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

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

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

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

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

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

$$c_t = \sum_j \lambda^j c_{jt} \quad l_t = \sum_j \lambda^j l_{jt} \quad k_t = \sum_j \lambda^j k_{jt} \quad 0 = \sum_j \lambda^j b_{jt}$$

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

B.2 Conditional Expectations and Average Expectations

Given Proposition B.3 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

$$\mathbb{E}_{jt}\left[\eta_{t+1}\right] = \alpha_{j0} + \alpha_{j1}s_{jt} + \alpha_{j2}\overline{\mathbb{E}}_{jt} \tag{B.15}$$

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

$$s_{jt} = \eta_{t+1} + e_t^F + \sigma_{jt}\epsilon_{jt} \tag{B.16}$$

Using (B.15)-(B.16) 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

$$\overline{\mathbb{E}}_{jt} = \frac{\alpha_{j0}}{1-\alpha_{j2}} + \frac{\alpha_{j1}}{1-\alpha_{j2}}\eta_{t+1} + \frac{\alpha_{j1}}{1-\alpha_{j2}}e_t^F + \frac{1}{1-\alpha_{j2}}\varepsilon_t \tag{B.17}$$

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

$$\overline{\mathbb{E}}_{jt} = \pi_{j0} + \pi_{j1}\eta_{t+1} + \pi_{j2}e^F_t + \pi_{j3}\varepsilon_t \tag{B.18}$$

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

$$\begin{bmatrix} \eta_{t+1} \\ s_{jt} \\ \overline{\mathbb{E}}_{jt} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \\ \pi_{j0} \end{bmatrix}, \begin{bmatrix} \sigma^2_\eta & \sigma^2_\eta & \pi_{j1}\sigma^2_\eta \\ \sigma^2_\eta & \sigma^2_\eta + \sigma^2_e + \sigma^2_{jt} & \pi_{j1}\sigma^2_\eta + \pi_{j2}\sigma^2_e \\ \pi_{j1}\sigma^2_\eta & \pi_{j1}\sigma^2_\eta + \pi_{j2}\sigma^2_e & \pi_{j1}\sigma^2_\eta + \pi_{j2}\sigma^2_e + \pi_{j3}\sigma^2_\varepsilon \end{bmatrix} \right) \tag{B.19}$$

Using the Bayes theorem, one obtains a system of equations that depends on πs 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.

B.3 Recursive Equilibrium

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 (29), 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*

$$f_{jt} = f\left(S_t, \mathcal{E}_{jt}\left[\eta^L_{t+1}\right], \mathcal{E}_{jt}\left[\eta^S_{t+1}\right]\right) \tag{B.20}$$

2. *Aggregate variables and prices depend on the economy's current state and the average*

expectations but not on households' individual conditional expectations. Then

$$f_t = f(S_t) \tag{B.21}$$

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 which arises as an invertible function of some price or aggregate variable in the economy. 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.*

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.

Proof. 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 follows

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

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, continuously differentiable. I'm using the fact that $S_t \subset S_{jt}$ when taking the conditional expectation; however, when deriving the individual optimal 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 $f_2\left(\cdot,\cdot\right)$ 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 $f_2\left(\cdot,\cdot\right)$. 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 follows

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

the coefficient $\hat{f}_{kh}$ 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 any general variable for the representative household will be obtained by aggregating across all agentes that belong to this household

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

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.

C. Data

C.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 equipment (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 is 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.

C.2 Financial uncertainty shocks

I use the measure of financial uncertainty shocks provided by Ludvigson, Ma, and Ng (forthcoming). Specifically, they construct statistical uncertainty indices using the methodology of Jurado, Ludvigson, and Ng (2015). For instance, in the case of financial uncertainty U_{Ft}, the framework aggregates a large number of financial indicators $y^F_{jt} \in Y^F_t = \left(y^F_{1t}, \cdots, y^F_{Nt}\right)'$. Its $h-$period ahead uncertainty is denoted by $\mathcal{U}^C_{jt}(h)$. This measure is defined to be the volatility of the unforecastable component of the future value of this variable, conditional on the information set at period t. Formally, the financial uncertainty index of variable y^F_{jt} is

$$\mathcal{U}^F_{jt}(h) \equiv \sqrt{\mathbb{E}\left[\left(y^F_{jt+h} - \mathbb{E}\left[y^F_{jt+h}|I_t\right]\right)^2|I_t\right]}$$

where I_t is the information set available at period t. Financial uncertainty is an aggregate of individual uncertainty series, that is

$$\mathcal{U}_{Ft}(h) \equiv \text{plim}_{N\to\infty}\sum_{j=1}^{N}\frac{1}{N}\mathcal{U}^F_{jt}(h)$$

To construct the measures of macroeconomic and financial uncertainty ($\mathcal{U}_{Mt}$ and $\mathcal{U}_{Ft}$, respectively), they use 134 macroeconomic variables and 148 monthly financial indicators, both for the period 1960:07 - 2015:04. Then, they estimate a three-variable structural VAR that includes both uncertainty indices and a measure of real economic activity. Finally, they obtain the residuals from the structural VAR which represent the shocks. Figure 2 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.

C.3 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 weights for this sample. However, there is a concern about whether this survey is representational since it may not capture appropriately the post-1968 inflow of immigrants to the United States (see Heathcote, Perri, and Violante (2010)).

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, savings, and bonds (W_{it}^{csb}), including checking or savings accounts, money market funds, certificates of deposit, government savings bonds, and treasury bills; stocks (W_{it}^{sto}), which includes 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. The PSID asks the following questions:

- Business assets (W_{bus}^{peq}): *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_{it}^{saf}): *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 pen-*

sions 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_{it}^{sto}): *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 following 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. I define gross financial, non-financial wealth and debt as follows

$$W_{it}^{fin} = W_{it}^{csb} + W_{it}^{sto} + W_{it}^{ira} + 0.5 * W_{it}^{oth}$$

$$W_{it}^{nof} = W_{it}^{peq} + W_{it}^{hou} + W_{it}^{ore} + 0.5 * W_{it}^{oth}$$

$$D_{it}^{tot} = D_{it}^{hou} + D_{it}^{oth}$$

Since W_{it}^{oth} includes financial components and non-financial components, I split it equally between financial and non-financial wealth. Given these definitions, gross wealth and net wealth are computed as follows

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

Table A.5 presents the portfolio composition across the distribution of net worth. The table presents evidence that the portfolio of the bottom 50% is concentrated in private residences and safe assets (checking, saving accounts, and bonds). Moreover, these individuals are highly leveraged. As individuals move toward the upper part of the net worth distribution, stocks and private equity become more important. Housing and CBS assets are still significant, 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. As Table A.6 shows, around 60% of individuals in the PSID own a house. However, if one only considers individuals not owing a house, the fact that wealthier individuals hold higher positions in riskier assets remains. Panel C of Table A.5 presents the portfolio composition for renters in the survey. Individuals in the bottom 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 comes from the feature that this measure includes IRAs.

Moving on to the income variables, the survey provides information about the reference person and their 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

Table A.5: **Portfolio composition**

	Gross wealth shares				Leverage ratio mort.	Log gross wealth
	Financial wealth		Non-financial wealth			
	CSB	Stocks	Housing	Pri. Bus.		
Panel A: 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
Panel B: 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
Panel C: 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 60%. The sample spans the period 1986 - 2017.

last three decades (see Panel B of Figure 5). For this reason, I compute the ratio between house value and rent ($r^h_{is,2017}$) for homeowners i in state s in the last survey wave; I then calculate the weighted (house value) average using properties with 2-12 rooms for each state; finally, I apply the national grow rate of the price-rent ratio for the previous years. I use these state-level ratios and the individual house value to compute a measure of imputed rent ($\widehat{y}^{rent}_{it}$). The PSID does not provide information on stock capital gains (g^{sto}_{it}), which turns out to be very important in explaining saving behavior across the distribution[31]. Without other

[31] Fagereng, Blomhoff Holm, Moll, and Natvik (2019) use 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

sources to obtain a measure of capital gains, I construct this variable as $g^x_{it} = W^x_{it} - W^x_{it-1}$. The PSID also includes information on mortgage payments, y^{mort}_{it-1}; however, it does not include information on payments for 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 payments on other types of debt, I label this as y^{odebt}_{it-1}. 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

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

Net income is defined as follows

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

Table A.6 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 case of wealth variables, I assume an equal split between reference person and spouse.

households own assets that experience persistent capital gains and that they hold them in their portfolio instead of realizing the gains

Table A.6: **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.

C.4 Surveys of consumers - University of Michigan

The SOC is a national survey statistically designed to be representative of all American households. The individual level data of the SOC spans the period January 1978 to September 2020. Each month, a minimum of 500 interviews are conducted by landlines and/or cell phones and around 50 core questions are answered. In total, the samples includes around

300,000 individual-month observations. Table A.7 presents the variables used in this paper.

To merge the SOC with the PSID, I use the variables in Panel A of Table A.7. The PSID provides state codes (51 categories); so I compile them into the five categories provided by the SOC using the state by region[32] definition. I then create two variables in both surveys to account for individuals with high-school and college. Finally, I create income quintiles in the PSID using the before-tax total income.

Before the merging process, the PSID has around 70,000 observations with non-missing returns to net worth and around 67,000 observation with non-missing returns to financial wealth. After the merging, I end up with around 34,000 observations without missing returns to net worth and 32,000 with non-missing returns to financial wealth.

Table A.7: **Surveys of consumers: data details**

Variable	Description	Question	Value
Panel A: merging variables			
YYYY	Year		1986 - 2017
YTL5	Income quintiles		1: Btm. 20%; 2: 21-40%; 3 41-60%; 4: 61-80%; 5: Top 20%
HOMEOWN	Home ownership	Do you (and your family living there) own your own home, pay rent, or what?	1: owns or is buying; 2: rent; 99: NA
INVEST	Stocks ownership	The next questions are about investments in the stock market. First, do you (or any member of your family living there) have any investments in the stock market, including any publicly traded stock that is directly owned, stocks in mutual funds, stocks in any of your retirement accounts, including 401(K)s, IRAs, or Keogh accounts?	1: yes 5: no

[32] See https://data.sca.isr.umich.edu/fetchdoc.php?docid=29608.

AGE	Age of Respondent		1 - 96 97: 97 or older
REGION	Region of Residence		1: West 2: North Central 3: Northeast 4: South
SEX	Sex of Respondent		1: Male; 2: Female
MARRY	Marital status of respondent	Are you currently married, (living with a partner), separated, divorced, widowed, or have you never been married?	1: married/partner; 2: separated; 3: divorced; 4: widowed; 5: never married
NUMKID	Number of children <18	How many members of your household are 17 years of age or younger?	0 - $\sim$
EDUC	Education of respondent		1: Grade 0-8 no hs diploma; 2: Grade 9-12 no hs diploma; 3: Grade 0-12 w/ hs diploma; 4: Grade 13-17 no col degree; 5: Grade 13-16 w/ col degree; 6: Grade 17 W/ col degree
Panel B: analysis variables			
BEXP	Economy better/worse next year	And how about a year from now, do you expect that in the country as a whole business conditions will be better, or worse than they are at present, or just about the same?	1: better a year from now; 3: about the same; 5: worse a year from now; 8: DK; 9: NA

NEWS1-2	Exposure to news categories	During the last few months, have you heard of any favorable or unfavorable changes in business conditions? What did you hear?	33,73: money, credit, and interest rates; 35,74: firms' profits; 36,76: stock market
PSTK	Subjective % change of investment	What do you think is the percent chance that a one thousand dollar investment in a diversified stock mutual fund will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?	0 100%; 998: DK; 999: NA
WT	Household Head Weight (Mean=1)		