Household Consumption and Dispersed Information*

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Abstract

By introducing an information friction to a heterogeneous agent model, we are able to explain two patterns of small economies experiencing large income changes: (1) excess volatility in consumption and (2) household consumption elasticities that have low correlation with income. With a standard dispersed information structure, households cannot distinguish aggregate income shocks from idiosyncratic ones. Their consumption responds excessively to aggregate shocks, which they incorrectly forecast to be too persistent. This effect occurs homogeneously across the income distribution, lowering the correlation of the consumption elasticity with income. We corroborate our central mechanism using survey data on household expectations of their future earnings.

JEL-Codes: D84, E21, E32

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1 Introduction

Why is aggregate consumption so volatile? This is a classic question in macroeconomics. Traditional models with full information and rational expectations (FIRE) predict that consumption will be relatively inelastic to aggregate income changes, as households smooth consumption (Kydland and Prescott, 1982). However, consumption volatility is much higher than expected, even more so in developing open economies (Aguiar and Gopinath, 2007). Hypothesized explanations are abundant in the literature, but recent evidence narrows down the possibilities. Guntin et al. (2023) (hereafter GOP) show that a subset of models where financial frictions drive consumption volatility predict that across households, the elasticity of consumption to an aggregate income shock should decrease with household income.[1] Yet, GOP document that the consumption elasticity to large macroeconomic shocks remains high across the entire income distribution, using household-level consumption data from four small open economies.[2] They conclude that consumers of all income levels appear to respond as if changes to aggregate income are permanent shocks.

We propose an explanation that is consistent with the finding by GOP: households face an information friction. Specifically, households are unable to accurately distinguish idiosyncratic income shocks from aggregate income shocks. Crucially, the idiosyncratic component of household income is more persistent than aggregate income. Therefore, if household income rises due to an aggregate shock, households will expect their income improvement to be more persistent than if they had full information. Households respond by increasing consumption by more than if they correctly predicted that the income improvement would be short-lived.

We study this mechanism in a tractable heterogeneous agent model with a standard

[1] Like Guntin et al. (2023), we are careful to distinguish the distribution of consumption elasticities to aggregate income shocks from the distribution of marginal propensities to consume (MPCs), which are elasticities to unexpected idiosyncratic windfalls. Empirical evidence is clear that the MPCs to transitory income shocks are decreasing with income and especially household liquidity. For example, Johnson et al. (2006) document this pattern in the response to 2001 tax rebates, Parker et al. (2013) do the same for 2008 stimulus checks, as do Chetty et al. (2020) for COVID-19 relief. These relationships with income are consistent with standard theories, including our own. Kaplan and Violante (2014) augment a standard theory to explain why liquidity matters more than income or wealth.

[2] GOP study a class of models with financial frictions that attribute large declines in consumption to transitory declines in income and a tightening in financial conditions (see Mendoza (2005, 2010), and Eggertsson and Krugman (2012) for examples). They show that models with these features predict that the consumption elasticity with respect to an aggregate income shock should decrease with household income. However, GOP note that settings in which negative transitory shocks can lead to near-permanent effects on economic activity can generate consumption patterns similar to the ones they document. Examples include Benigno and Fornaro (2018), Ma (2020), Queralto (2020), Benguria et al. (2022), and Gornemann et al. (2024). A common feature is a distortion in production and innovation decisions caused by the interaction of financial frictions or liquidity traps with transitory shocks.

dispersed information structure. Households in a small open economy receive stochastic income, and solve a standard consumption-savings problem to mitigate their income risk and smooth consumption over time. Income is determined by two stochastic components: a very persistent idiosyncratic income process, and a less persistent common aggregate income process.[3] Households have rational expectations, but incomplete information. They do not directly observe aggregate income shocks, and so cannot accurately distinguish between the two components, which distorts their consumption and savings decisions. We find that the volatility of aggregate consumption growth is one half larger when agents face the information friction. The additional risk induces a stronger precautionary savings motive, so average savings is 35% higher than the full information baseline. And while consumption is more volatile, the elevated wealth also increases the average consumption level.

In the cross-section, we also recover results that are in line with GOP's finding of relatively homogeneous consumption responses to income shocks. Specifically, we document that the consumption elasticity to aggregate income is larger and more homogeneous across the income distribution when agents face information frictions, where the slope of the consumption elasticity across log income levels is nearly zero. This is the first of several results that require studying incomplete information and heterogeneous agents in a unified framework. Moreover, we find that the information friction and financial friction interact in a variety of rich ways: the frictions jointly attenuate inequality dynamics, reduce the sensitivity of the wealth distribution to the borrowing constraint, reverse the relationship between idiosyncratic risk and the aggregate consumption elasticity, and generate endogenous correlations between aggregate forecasts and wealth.

Is our information friction realistic? To answer this question, we turn to survey data on household expectations, and document evidence corroborating our central mechanism. The main implication of the information friction is that the response of households forecasts of their own income should respond with the same elasticity to aggregate and idiosyncratic income shocks. If instead households have full information, then their forecasts will be *less elastic* to aggregate than to idiosyncratic shocks. This is a testable prediction. We employ data on household forecasts from the NY Fed's Survey of Consumer Expectations, and decompose household income into aggregate and idiosyncratic components at the state level. Our results are clear: household forecasts are *at least as elastic* to aggregate shocks as to idiosyncratic shocks. Thus we confirm that GOP's characterization of consumption behavior

[3] A large literature studying household income dynamics finds a persistent component of idiosyncratic earnings that is highly autocorrelated (Heathcote et al., 2010), a finding that is confirmed in recent work with administrative data (Guvenen et al., 2021), and which we establish using the Panel Study of Income Dynamics (PSID). The autocorrelation is so high, that it is often modeled as a random walk (Blundell et al., 2008). In contrast, aggregate earnings exhibit faster reversion to trend, which we document in Appendix A.

applies to household expectations as well: consumers' forecasts respond to aggregate income changes as if they are more persistent than they really are.

Our paper contributes to several strands of the literature. First, we join a small but promising new literature that synthesizes incomplete information theories with heterogeneous agent models. Broer et al. (2021) and Broer et al. (2022) depart from the standard FIRE structure by introducing a rational inattention decision that is endogenously heterogeneous.[4] Angeletos and Huo (2021) show that myopic effects of information frictions are exacerbated by the MPC distribution typical of HANK models. Gallegos (2022) extends Bilbiie (2020) to study a linear HANK model with dispersed information.[5]

Second, we contribute to the empirical literature on systematic errors in expectations revealed in survey data. We join a large group of papers studying errors in households forecasts of their own outcomes. Most closely related, Rozsypal and Schlafmann (2023) use forecast errors of household income from the Michigan Survey of Consumers and find that households overestimate the persistence of their own income and are too pessimistic about aggregate income.[6] We also join a small group of papers that examines the effects of aggregate shocks on forecasts of idiosyncratic variables. We study households, while many of these papers concern firms. For example, Andrade et al. (2022) and Adams et al. (2024) study how firms' forecasts of their own prices and production respond to aggregate and industry-level shocks, finding support for the standard dispersed information structure.[7]

Third, we contribute to a class of heterogeneous agent models attempting to understand large consumption responses to income. While we follow GOP and study the consumption-income elasticity to aggregate shocks, many more papers focus on explaining large MPCs. We consider our explanation of the consumption-income elasticity to be complementary to this literature, which Kaplan and Violante (2022) survey. While our simple model cannot explain the cross-sectional evidence on consumption out of idiosyncratic windfalls, our large consumption elasticities to aggregate shocks are relevant for many of the same aggregate

[4] Other papers depart from FIRE in heterogeneous agent models by relaxing rational expectations rather than of full information. For example, Auclert et al. (2020) and Carroll et al. (2020) assume agents have sticky expectations, in the style of Mankiw and Reis (2002) and Carroll (2003). Exler et al. (2020), Rozsypal and Schlafmann (2021), and Balleer et al. (2021) assume that agents form expectations with incorrectly specified models of their stochastic incomes.

[5] Angeletos and Lian (2016) survey the broader literature of incomplete information in macroeconomics. See Heathcote et al. (2009), Quadrini and Ríos-Rull (2015), Krueger et al. (2016) for broad surveys of the household heterogeneity models, and Kaplan and Violante (2018) for a more recent survey that includes HANK features.

[6] Other work studying errors in workers expectations of their own labor market outcomes includes Balleer et al. (2021), Mueller et al. (2021), and Adams-Prassl et al. (2023). Mueller and Spinnewijn (2021) survey this literature more generally.

[7] Born et al. (2023) survey additional work on firms' forecasts of production and prices.

applications.[8] One advantage of our approach is that we attain large consumption-income elasticities, while maintaining a wealth distribution that does not suffer from the "missing middle" problem that Kaplan and Violante identify as plaguing most single asset models that otherwise achieve large MPCs.

The remainder of the paper is organized as follows. In Section 2 we describe our model, including the structure and intuition for the information friction. Section 3 describes our main results and equilibrium behavior in the model. In Section 4 we explore the interactions between the information and asset market frictions. Section 5 documents the empirical evidence corroborating our information friction. Section 6 concludes.

2 Model

In this section we describe our baseline model. Heterogeneous agents trade risk-free assets in a small open economy in order to self-insure against income risk and smooth consumption. The agents face a standard friction: dispersed information in the style of Lucas (1972) that prevents them from observing the aggregate state of the economy.

2.1 Households

There is a unit measure of identical and infinitely lived households. Households are indexed by i and time is indexed by t.

The household's preferences over current and future consumption are represented by the utility function

$$\mathbb{E}_{i,t}\left[\sum_{s=0}^{\infty}\beta^s\frac{C_{i,t+s}^{1-\gamma}-1}{1-\gamma}\right] \tag{1}$$

where $C_{i,t}$ is the household's consumption in period t, β is its discount factor, and γ is the coefficient of relative risk aversion. Households have rational expectations, but incomplete information. The expectation operator $\mathbb{E}_{i,t}$ is conditional on household i's information set $\Omega_{i,t}$. Thus the only distortion to households' forecasts is due to the information friction; given their information, households have rational expectations.

The household receives stochastic income $Y_{i,t}$, which in logs is the sum of a mean zero idiosyncratic component $Y_{i,t}^I$ and a common aggregate component Y_t^G:

$$\ln Y_{i,t} = \ln Y_{i,t}^I + \ln Y_t^G \tag{2}$$

[8] This includes monetary policy (Kaplan et al., 2018), fiscal policy (Auclert et al., 2018), and aggregate shocks in general (Bilbiie, 2020) among others.

The idiosyncratic and aggregate components each follow an AR(1) process:

$$\ln Y_{i,t}^I = \rho_I \ln Y_{i,t-1}^I + u_{i,t}^I \qquad \ln Y_t^G = \rho_G \ln Y_{t-1}^G + u_t^G \tag{3}$$

with $u_{i,t}^I \sim N(0, \sigma_I^2)$, $u_t^G \sim N(0, \sigma_G^2)$, $\rho_I \in (0,1)$, and $\rho_G \in (0,1)$. Crucially, we assume $\rho_I > \rho_G$ so that the idiosyncratic component is more persistent than the aggregate component.

Household log income $\ln Y_{i,t}$ is the sum of independent AR(1) processes, so $\ln Y_{i,t}$ is an ARMA(2,1). Appendix B derives the parameters of this composite time series.

The household may hold a risk-free asset A_t which pays exogenous interest rate r. The household's budget constraint is

$$Y_{i,t} + (1+r)A_{i,t} = C_{i,t} + A_{i,t+1} \tag{4}$$

with $A_{i,t+1} \geq 0$ for $t \geq 0$. This implies that households cannot borrow.

2.2 The Information Friction

Households do not observe the incomes or choices of any other households, nor of the aggregate economy. They observe their income $Y_{i,t}$ but cannot independently observe the idiosyncratic and aggregate components $Y_{i,t}^I$ and Y_t^G. Thus if their income rises, they are unsure to what extent the increase was specific to them or economy-wide. Formally, the household's information set evolves by

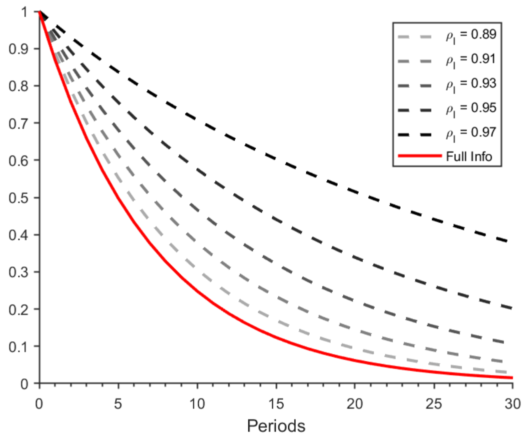
$$\Omega_{i,t} = \{\Omega_{i,t-1}, Y_{i,t}, A_{i,t}\} \tag{5}$$

Every period, households observe one new signal $Y_{i,t}$ determined by the two realizations $Y_{i,t}^I$ and Y_t^G. Even though households have rational expectations and know the parameters of the model, they cannot determine the realization of either the idiosyncratic or aggregate component with certainty. And because there are more new shocks that new signals every period, they can never learn exactly whether past changes to their incomes were driven by aggregate or idiosyncratic factors.[9] This imperfect backcasting reflects real world behavior; even if agents do not face literal information frictions, they act as if they do. Households are known to be inaccurate backcasters even for salient macroeconomic time series such as inflation (Jonung, 1981; Jonung and Laidler, 1988; Antonides, 2008; Axelrod et al., 2018).

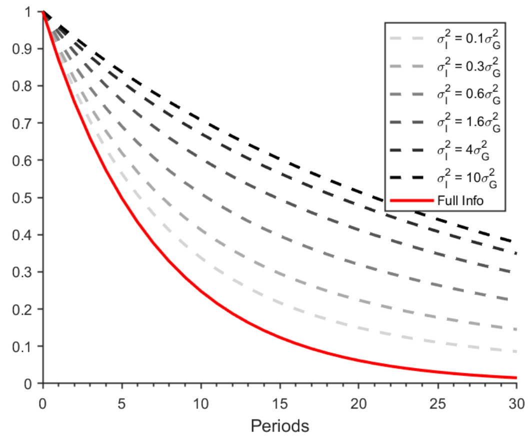
The information friction makes households over-estimate the persistence of an aggregate income shock. The autocorrelation of the aggregate income component ρ_G is less than

[9] Appendix B.6 demonstrates this mathematically.

that of the idiosyncratic income component ρ_I. The sum of the two components, which is observed by households, has an autocorrelation between ρ_G and ρ_I: individual income is more persistent than aggregate income. So when there is an aggregate income shock and households cannot tell that the shock is aggregate, they expect their income to change more persistently than they would if they had full information.



(a) Different Idiosyncratic Persistences



(b) Different Idiosyncratic Variances

Figure 1: Income Forecasts After Aggregate Shocks

Notes: Both panels plot the term structure of expectations after a unit aggregate income shock, with the aggregate autocorrelation set to $\rho_G = 0.8$. Panel (a) varies the idiosyncratic autocorrelation, with the relative idiosyncratic shock variance fixed at $\sigma_I^2 = 10\sigma_G^2$. Panel (b) varies the idiosyncratic shock variance, with the idiosyncratic autocorrelation fixed at $\rho_I = 0.95$.

Figure 1 demonstrates this over-estimation of an aggregate shock's persistence. This figure plots households' forecasts of their income multiple periods into the future after receiving an aggregate income shock.[10] The aggregate autocorrelation is $\rho_G = 0.8$; when households have full information, they correctly forecast their future income which decays relatively rapidly (the solid red curves).

The information friction matters most when the aggregate and idiosyncratic autocorrelations are most dissimilar. Panel (a) plots forecasts under incomplete information for different idiosyncratic autocorrelations ρ_I. When $\rho_I = \rho_G$, the information friction has no effect and households' forecasts are equivalent to the full information forecasts. When ρ_I is larger, individual income is more persistent, so households' forecasts of future income decay more slowly, and their expectations diverge from the full information case.

The information friction also has larger effects when the idiosyncratic shock has a larger variance. The autocorrelation of individual income is somewhere between those of the ag-

[10]Appendix B.4 derives expressions for these forecasts.

gregate and idiosyncratic components, and when the idiosyncratic component has a larger variance, its larger autocorrelation makes individual income more persistent. Panel (b) plots this effect for different idiosyncratic shock variances σ_I^2, while the other parameters are held at $\rho_G = 0.80$, $\rho_I = 0.95$, and the aggregate shock variance is $\sigma_G^2 = 1$. When σ_I^2 is larger, the idiosyncratic process has higher weight in determining income which becomes more persistent, and forecasted income decays more slowly. When σ_I^2 is small, household income is mostly driven by the aggregate process so households forecast accurately after an aggregate shock; as σ_I^2 goes to zero, the effect of the information friction disappears.

2.3 Equilibrium Definition

Given infinite sequences of exogenous variables $\{Y_{i,t}, Y_t^G, Y_{i,t}^I, u_t^G, u_{i,t}^I\}$ for all $i \in \mathcal{I}$, a competitive equilibrium in this economy consists of infinite sequences of allocations $\{C_{i,t}, A_{i,t}\}$ for all $i \in \mathcal{I}$; and information sets $\Omega_{i,t}$ for all $i \in \mathcal{I}$ such that:

1. Households maximize utility (1), subject to the budget constraint (4) and the no-borrowing constraint.
2. Income is determined by (2) and (3).
3. Information sets evolve according to (5).

3 Quantitative Analysis

In this section we document the model behavior. The information friction raises consumption volatility and nearly eliminates the correlation between household income and their consumption elasticity to aggregate shocks.

3.1 Calibration

We calibrate the model to match features of U.S. states, which we treat as small open economies. The time frequency is annual, and we set the world annual real interest to 2%. The discount factor β is set to be 0.945 in order to match the U.S. ratio of net worth to labor income in the National Income and Product Accounts (NIPA) and the Federal Reserve's Flow of Funds Tables. The risk aversion parameter γ is equal to 1 so that agents have a log utility function. To parameterize the aggregate income shock process, we use the U.S. NIPA accounts to estimate a state-level aggregate income process (Appendix A). We find that the autocorrelation is approximately 0.87 and the standard deviation is roughly 0.03.

These statistics define the values for ρ_G and σ_G. For the stochastic process for idiosyncratic income, we set the values of ρ_I and σ_I to match the income dynamics estimated by Guvenen et al. (2021), which implies $\rho_I = 0.97$ and $\sigma_I = 0.19$.[11] Table 1 summarizes our baseline calibration.[12]

Parameter	Interpretation	Value	Reference
β	Discount factor	0.945	U.S. net-worth-to-earnings ratio of 8
r	Real interest rate	0.02	Standard value
γ	Risk aversion	1	Standard value
ρ_I	Persistence of idiosyncratic income shock	0.97	Guvenen et al. (2021)
σ_I	Standard deviation of idiosyncratic income shock	0.19	Guvenen et al. (2021)
ρ_G	Persistence of aggregate income shock	0.87	NIPA
σ_G	Standard deviation of aggregate income shock	0.03	NIPA

Table 1: Calibration

The discretization of the stochastic processes for idiosyncratic and aggregate income is different for the full information and the incomplete cases. As shown in Appendix B.1, the income process in the incomplete information case follows an ARMA(2,1) process. We express this process as a VAR(1) and then use Tauchen (1986)'s approach. We solve the model using a variation of Coleman (1990)'s time iteration method. See Appendix C.1 for more details about the solution method or grids. We consider an asset grid with a zero lower bound for assets, so that in the baseline calibration agents are not able to borrow.

3.2 Main Results

3.2.1 Long-run Moments

In order to assess the role of incomplete information we compare the two models in terms of their long-run moments, and in the way agents respond to idiosyncratic and aggregate income shocks. Using the policy functions we simulate an economy composed of 2,000 individuals for 10,000 periods. We simulate this economy with both incomplete and full information,

[11] This calibration contrasts with that of Pischke (1995), who estimates that idiosyncratic income is *less* persistent than aggregate income. This leads to the opposite conclusion as our analysis: the information friction causes aggregate consumption to be *less* volatile. The difference in calibration is due to two factors. First, Pischke uses household incomes reported in the Survey of Income and Program Participation, which features more measurement error than the Social Security Administration data that Guvenen et al. (2021) have access to. Second, Pischke estimates MA processes in differences, while the estimates in our calibration are ARMA processes in levels.

[12] We explore alternative calibrations in Appendix F. First, we recalibrate the interest rate in the full information model to target the same asset-to-income ratio as the incomplete information case, rather than selecting a common interest rate. Then, we explore relaxing the borrowing constraint and adjusting the contribution of idiosyncratic risk. Across these exercises, none of our qualitative conclusions change, although we document additional ways that our information and financial frictions interact.

employing the same sequences of shocks in each simulation. Table 2 presents a summary of the long-run moments of aggregate and cross-sectional moments of the two models.

	Full Information	Incomplete Information
Aggregate Dynamics		
Consumption: Standard Deviation (log change)	0.0079	0.0121
Consumption: Autocorrelation	0.979	0.952
Assets: Standard Deviation (log change)	0.0066	0.0038
Assets: Autocorrelation	0.997	0.997
Cross-Sectional Statistics		
Income: Mean	1.38	1.38
Income: Coefficient of Variation	0.95	0.95
Consumption: Mean	1.55	1.60
Consumption: Coefficient of Variation	0.80	0.79
Consumption: Autocorrelation	0.99	0.99
Assets: Mean	8.18	11.06
Assets: Coefficient of Variation	1.46	1.19
Assets: Autocorrelation	1.00	1.00

Notes: Long-run moments are calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models.

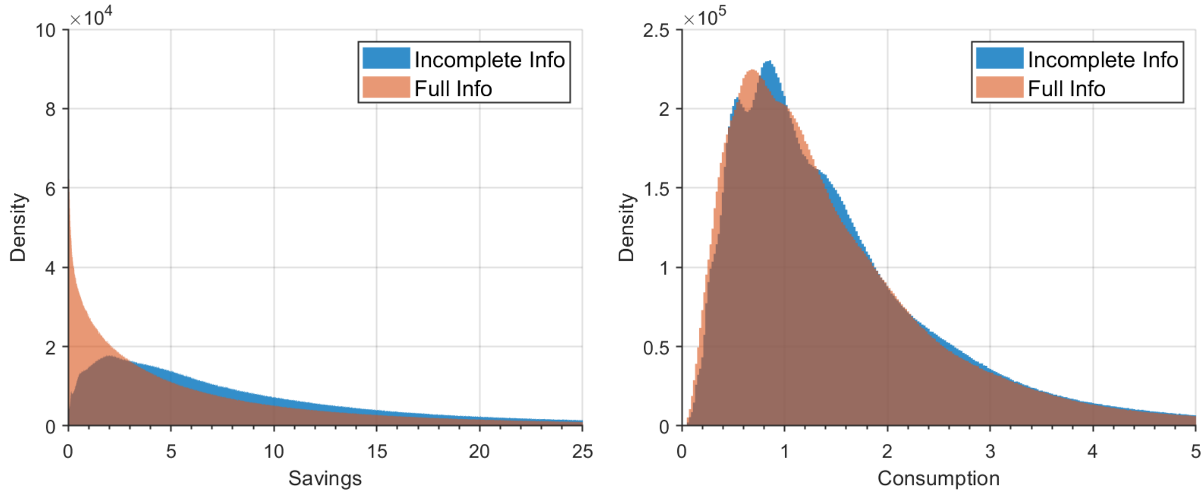
Table 2: Long-run Moments

The simulated statistics of Table 2 reveal how the information friction distorts consumption decisions. Aggregate consumption growth is 53% more volatile under incomplete information, because households undersave in response to aggregate income shocks, which they cannot distinguish from more persistent idiosyncratic shocks. Consumption is also less autocorrelated, reflecting that households are less effective at smoothing consumption. Because the incomplete information households forecast income less accurately, they have a stronger precautionary savings motive. Facing the same interest rate, they hold more assets than they would under full information. The additional financial income allows them to afford higher average consumption as well.

In the cross-section, the information friction distorts consumption and assets in different ways. The friction decreases wealth inequality because the increased precautionary savings motive is strongest at lower asset levels: poor households have stronger incentives to save and move away from the constraint, but rich households still act as if they are nearly unaffected by the constraint. This effect is clear in Figure 2 panel (a), which presents the ergodic distributions of aggregate assets for both models. The information friction distorts the distribution most for low asset levels: the full information model has much more mass near the borrowing constraint, but a similar right tail.[13]

[13]The full information model that we analyze is unable to generate realistic wealth inequality. This remains true when we introduce the information friction. Appendix F.2 considers an extension where the discount

In contrast, the friction has little effect on consumption inequality (Figure 2 panel (b)). All else equal, the lower wealth inequality would reduce consumption inequality. But this force is offset because households are less effective at consumption smoothing. Most of their income is driven by idiosyncratic shocks, to which households underreact in the short run, before appropriately increasing their consumption response once they realize that their income change was persistent. This delayed consumption response amplifies consumption dispersion because households with large shocks have additional savings to draw down as excess consumption. On net, the coefficient of variation for consumption is almost as large with the information friction as it is without, even though wealth is much more equally distributed.



(a) Assets

(b) Consumption

Figure 2: Ergodic Distributions - Full and Incomplete Information Models

Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. Both distributions extend outside the axis range, but the right tails are omitted for readability.

3.2.2 Consumption Volatility

Table 2 reports that the information friction increases aggregate consumption volatility. To understand why, this section compares how the two economies respond to income shocks.

Figure 3 presents the impulse response functions of consumption and assets to aggregate income shocks in panels (a) and (b).[14] The responses differ substantially across models.

factor is stochastic, following Krusell and Smith (1998). We show that the incomplete information case augmented by this feature can generate a reasonable wealth distribution. Crucially, we also show that the main quantitative conclusions we describe below still hold in this scenario.

[14] Appendix C.2 describes how we compute impulse response functions.

The response of aggregate consumption, on impact, is nearly 50% larger in magnitude when agents face information frictions. For assets we see the opposite behavior: agents save more in the full information setting. The full information case is the standard response that we would expect to see when agents react to transitory income shocks: upon receiving the income shock, consumption should increase modestly while most of the additional income should be saved. Under incomplete information, agents cannot initially distinguish if the income shock they are experiencing is an aggregate shock or the more persistent idiosyncratic shock, so their consumption responds much more, and their savings responds less. In short, under incomplete information agents tend to *undersave* in response to aggregate shocks, relative to full information.

Panels (c) and (d) present the impulse response functions of idiosyncratic consumption and assets to idiosyncratic income shocks, respectively. The relative responses to idiosyncratic income shocks have reversed across models: under incomplete information agents tend to save more of the income shock than under the full information scenario. This is because the idiosyncratic component of income is very persistent, so agents with full information increase their consumption nearly one-for-one. But with incomplete information, agents cannot tell if they have received the near-permanent idiosyncratic shock, or the less persistent aggregate shock. Therefore they *oversave* in response to idiosyncratic shocks, relative to full information.

So why does the information friction make aggregate consumption more volatile? Idiosyncratic shocks are mean zero in the population, so their effects on consumption wash out in the aggregate. Thus aggregate consumption is only determined by the aggregate income shocks, to which households undersave and overconsume.[15]

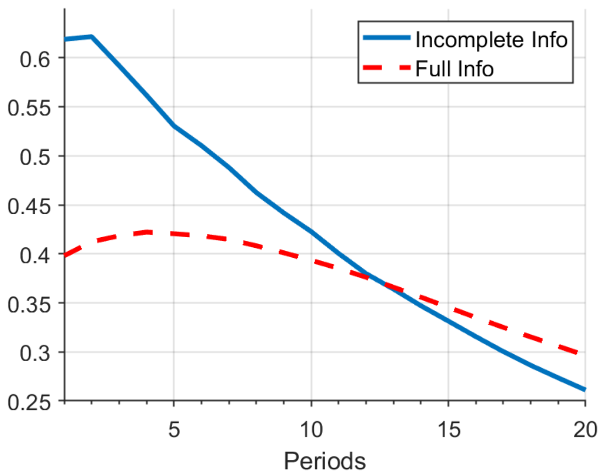
Thus far we have show that under incomplete information, consumption is more responsive to aggregate shocks. Is this effect heterogeneous? How does this consumption sensitivity vary across households? We explore these questions in the next section.

3.2.3 Elevation and Homogenization of Consumption Elasticities to Aggregate Shocks

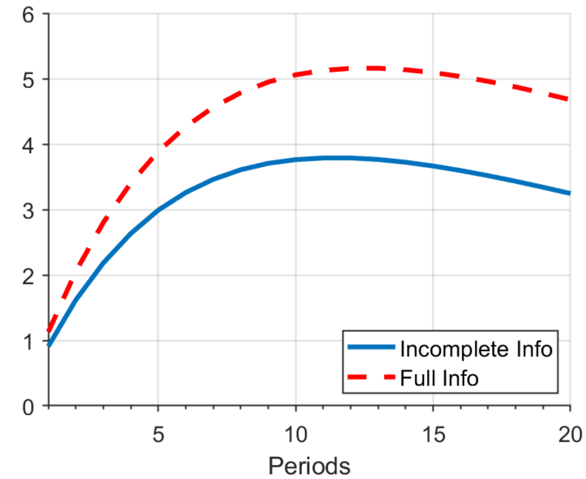
Guntin et al. (2023) find that the elasticity of consumption to aggregate shocks is both large and homogeneous across the income distribution.[16] In effect, households respond to

[15] This washing out of idiosyncratic shocks is the same mechanism by which aggregate noise shocks cause excess business cycle volatility in Adams (2023).

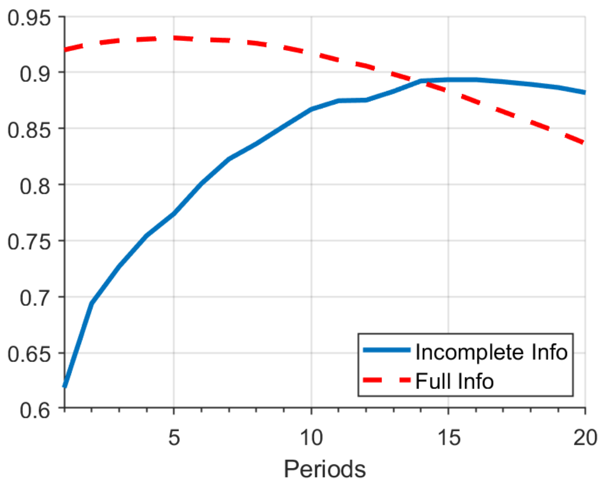
[16] GOP document this pattern in four small open economies with a range of income levels: Italy, Mexico, Peru, and Spain. In contrast, we calibrate the model treating US states as small open economies, because this is the setting in which we can test the model's predictions for forecasting behavior (Section 5). However, a reasonable concern is whether the large and homogeneous CIEs also characterize US states. In Appendix



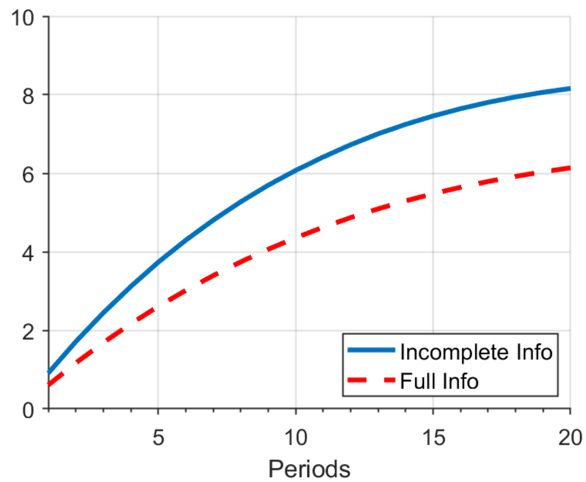
(a) Consumption IRFs to Aggregate Shock



(b) Asset IRFs to Aggregate Shock



(c) Consumption IRFs to Idiosyncratic Shock



(d) Asset IRFs to Idiosyncratic Shock

Figure 3: Impulse Responses to Income Shocks

Notes: Impulse response functions are calculated by subjecting the economy to an aggregate or idiosyncratic income shock consistent with a one standard deviation forecast error, and comparing with a counterfactual economy receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.

transitory aggregate shocks as if they perceive them to be permanent. This is exactly how the information friction in our model affects households. Thus, we find that introducing the information friction to a heterogeneous agent model *elevates and homogenizes consumption elasticities to aggregate income*.

To characterize this effect, we calculate the consumption-income elasticities to aggregate income. Like GOP, we focus specifically on large aggregate shocks, which in our model affects every agent across the income distribution proportionately.[17] The consumption elasticity to aggregate income Y_t^G for individual i at time t is

$$CIE_{i,t}^G = \frac{\log(C_{i,t}) - \log(C_{i,t-1})}{\log(Y_t^G) - \log(Y_{t-1}^G)} \tag{6}$$

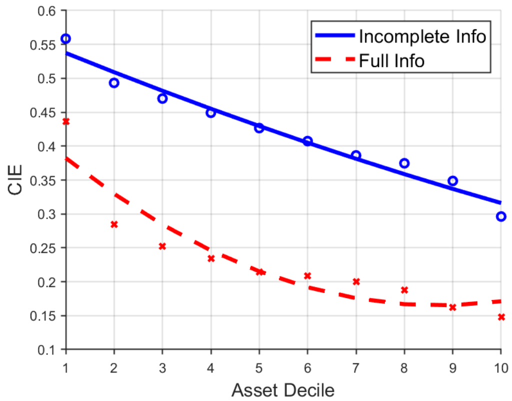
We calculate the elasticities for each agent in our simulation for each information structure. To ascertain the cross-sectional relationships with income and wealth, Figure 4 presents the within-decile averages of $CIE_{i,t}^G$, across models.[18] In both cases deciles are calculated from the ergodic distribution of the incomplete information model, so that levels are comparable across information structures.

The elasticity of consumption to aggregate income is elevated in the incomplete information model, where the average CIE^G is 0.42, versus 0.28 for full information. Figure 4 panel (a) plots the average elasticities within asset deciles, where the information friction (blue circles, with solid blue quadratic fit) substantially elevates the elasticities relative to full information (red crosses, with dashed red quadratic fit) across most of the asset distribution. The elasticities are only similar at very low levels of wealth, where agents have high elasticities because they are likely to be constrained.

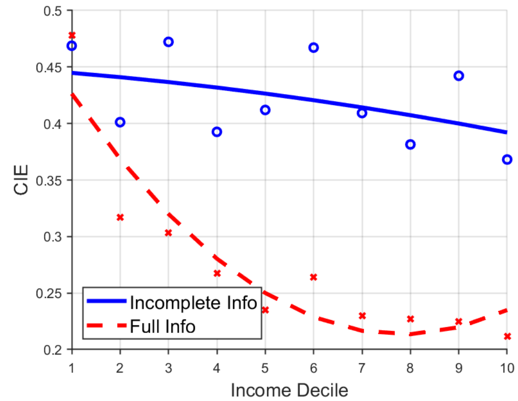
E.2.3, we investigate this concern using longitudinal data from the PSID, and find no evidence that this pattern fails to hold in the US.

[17]We consider aggregate income changes larger than two standard deviations, although our conclusions are not dependent on this particular threshold. In addition to following GOP, setting a threshold for income changes prevents us from occasionally calculating excessively large CIE's when the denominator happens to be small.

[18]In addition to these elasticities to aggregate shocks, we also calculate the consumption elasticities to generic income, and report their distribution in Appendix C.3.



(a) Elasticities by Wealth



(b) Elasticities by Income

Figure 4: Consumption-Income Elasticities to Aggregate Income

Notes: The solid and dashed curves are fit from quadratic regressions. The distributions of CIE^G are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. The elasticity is calculated at the household level and averaged within household groups corresponding to the asset or income deciles of the incomplete information model's ergodic distribution. Households are grouped based on their position in period $t-1$ for a shock that occurs in period t. The plotted elasticities only include periods with aggregate shocks exceeding two standard deviations in absolute value.

The information friction's homogenization effect is clear in the relationship between the consumption elasticity and household income (Figure 4 panel (b)). Homogenization occurs in panel (a) as well, but we focus on the relationship with income in order to mirror the findings by GOP: the consumption elasticity is homogeneously large across the income distribution, in contrast to the negative relationship implied by full information. Why does this occur? Under full information, the response is heterogeneous due to the financial friction; low wealth individuals are more elastic to transitory income shocks because they are near the borrowing constraint. However, the response becomes more homogeneous as income becomes more persistent; in the extreme case when all income shocks are permanent, all agents have the same unit elasticity. Thus under incomplete information where households perceive aggregate shocks as more persistent than they really are, they react more homogeneously.

Our results differ from GOP's findings in two ways. First, we show that the information friction elevates average CIE^G, but not to levels as large as GOP's estimates $(0.7-1.2)$. This is because agents in the model mistake aggregate income for idiosyncratic income, which in the conservative baseline calibration only has autocorrelation $\rho_I = 0.97$. If idiosyncratic income were more persistent, then the average CIE^G would be even larger. Second, in some countries GOP find that the relationship between the consumption elasticity and household income is distorted so much as to be upward-sloping in income. This is possible in our model for some alternative calibrations. In particular, when idiosyncratic income has a higher autocorrelation ρ_I, households mistakenly perceive aggregate shocks to be nearly permanent, which elevates elasticities enough to be increasing with income. We study this case in Appendix F.3.2.

3.3 Model Extensions

One assumption of the baseline model is that aggregate shocks affect all agents symmetrically. Is this assumption critical for information frictions to deliver homogeneous CIEs? In order to test the robustness of our model's predictions, we explore two extensions that feature heterogeneous effects of aggregate shocks: worker ex ante heterogeneity and unemployment. This section summarizes the extensions and our findings; Appendix D provides greater detail on the model setups, calibrations, solutions, and equilibrium properties.

3.3.1 Heterogeneous Skill Types

We now relax the assumption that all agents draw their income from the same stochastic process. Instead, we assume that there are K types of agents that have different elasticities to aggregate income. Agents of type k receive income determined by

$$\ln Y_{i,k,t} = \ln Y_{i,t}^I + \alpha_k^G \ln Y_t^G + \ln \kappa_k$$

where $Y_{i,t}^I$ and Y_t^G are the usual idiosyncratic and aggregate components. But now, type-k households differ in their elasticity α_k^G with respect to aggregate income. Thus, different types of households will have different sensitivities to aggregate income shocks. Additionally, κ_k controls the type-k households' average income level, so that sensitivity to aggregate shocks can explicitly vary across the income distribution.

To discipline the model, we assign agents to one of two types: skilled and unskilled. Then, using data from the CPS from 1977-2022, we calibrate the model to match the average skilled wage premium (2.21), the average share of skilled workers (0.49), and the elasticities of skilled and unskilled earnings to aggregate shocks (0.35 and 0.14, respectively).

Table 3 presents a summary of selected long-run moments for the baseline model and both extensions. When workers have heterogeneous skill types, our main conclusions hold: incomplete information increases consumption volatility, while elevating and homogenizing the CIE^G over the income distribution. Compared to the baseline, this extension has two main differences. First, aggregate volatility and risk are generally higher. This is because the higher income skill type is also more elastic to aggregate shocks. Second, the homogenization effect of the information friction is even stronger. Again, this is because skilled workers make disproportionately larger mistakes after an aggregate shock, and make up a disproportionate share of the high income deciles.

Moment	Baseline		Het. Skill		Unemployment	
	Full	Incomplete	Full	Incomplete	Full	Incomplete
Consumption Volatility	0.0079	0.0121	0.009	0.013	0.0079	0.0103
Assets Volatility	0.0066	0.0038	0.008	0.0042	0.0068	0.0047
Average CIE^G	0.28	0.42	0.33	0.45	0.27	0.31
Slope of CIE^G curve	-0.087	-0.023	-0.079	-0.002	-0.068	-0.017

Notes: Key moments for the baseline, heterogeneous skill types, and unemployment risk models are presented for both information structures. Consumption (assets) volatility corresponds to the standard deviation of log aggregate consumption (assets).

Table 3: Key Moments - Model Comparison

3.3.2 Unemployment

Another way that aggregate shocks can have heterogeneous effects across the income distribution is by affecting workers' extensive margin. To understand how this force affects our results, we modify agents' incomes to feature risk of job loss/entry. Crucially, these employment transition probabilities depend on aggregate log income. These probabilities are given by

$$s_t = \psi_s \ln Y_t^G + \overline{s} \qquad\qquad f_t = \psi_f \ln Y_t^G + \overline{f}$$

where s_t and f_t denote the separation and job-finding rate in period t. The parameters ψ_s and ψ_f control how the aggregate component of income affects transition into and out of unemployment. If agents only observe their own job loss, it would tell them nothing about the state of the aggregate economy. But correlated job losses tend to be salient, so we let agents observe noisy signals $z_{i,t}^s$ and $z_{i,t}^f$ of the economy-wide job loss and finding rates:

$$z_{i,t}^s = s_t - \overline{s} + \varepsilon_{i,t}^s \qquad\qquad z_{i,t}^f = f_t - \overline{f} + \varepsilon_{i,t}^f$$

with independent noise shocks $\varepsilon_{i,t}^s \sim N(0, \sigma_{\varepsilon^s}^2)$ and $\varepsilon_{i,t}^f \sim N(0, \sigma_{\varepsilon^f}^2)$. This complicates the signal extraction problem and adds multiple additional state variables, so to keep the model tractable, we assume that unemployed workers receive an unemployment benefit $bY_{i,t}$ that is proportional to the income they would receive were they to have a job.

To calibrate this extension, we use state-level transition data from JOLTS to estimate the parameters ψ_s, ψ_f, $\bar{s}$, and $\bar{f}$. To calibrate the noisy signals of the transition probabilities, we match empirical forecast error distributions using additional data from the SCE, which asks households to report expected probabilities that unemployment increases over a year. Otherwise, our parameterization is unchanged from the baseline model. In particular, this includes the parameters ρ_G and σ_G governing the aggregate earnings process Y_t^G. In the unemployment model, Y_t is now earnings *conditional on working*. A potential concern is that the low persistence of aggregate earnings in our baseline calibration could driven by workers moving along the extensive margin. In Appendix A we show this is not the case: aggregate earnings per employed worker has a similarly low autocorrelation.

The final columns of Table 3 report the effects of the information friction with the unemployment extension. As before, the information friction increases aggregate consumption volatility, and elevates and homogenizes the slope of the CIE curve. However, the effects are attenuated relative to the baseline model. This is because the information friction is weaker in the unemployment model. Households have additional information, as their noisy signals of transition probabilities inform them about the aggregate state of the economy through. With improved forecasting, agents make smaller mistakes, weakening the main mechanism by which the friction amplifies the effects of aggregate shocks.

4 Interactions Between the Frictions

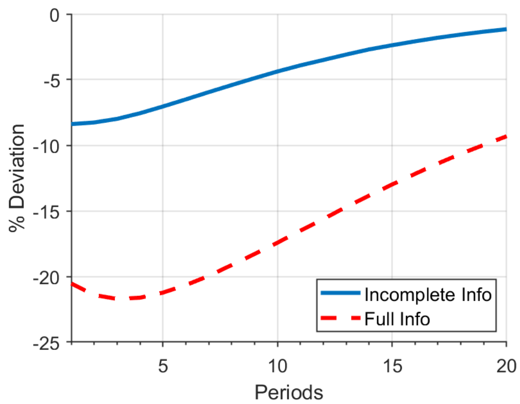
The main purpose of introducing dispersed information into a heterogeneous agents framework was to understand how the information friction affect distributions, particularly the elevation and homogenization documented by GOP, but also the general patterns of consumption and wealth inequality that we discuss in Section 3.2.

However, the information friction and the financial friction interact in rich ways. In this section, we show that the information friction attenuates the dynamics of wealth and consumption inequality, while also introducing new cross-sectional heterogeneity, skewness, and correlations for household forecasts. Additionally, in Appendix F we conduct a sensitivity analysis, and learn that the information friction also attenuates the effects of the financial friction on the wealth distribution, and reverses the effects of idiosyncratic risk on the aggregate consumption elasticity.

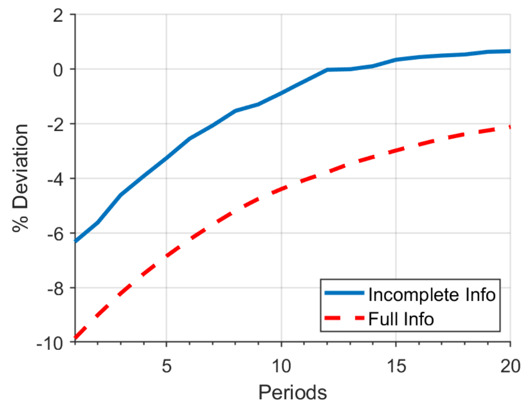
4.1 Inequality Dynamics

One valuable feature of heterogeneous agent models is the ability to study the dynamics of inequality. Introducing the information friction changes these dynamics in nontrivial ways. To demonstrate these effects, Figure 5 plots the average response of inequality measures to an aggregate income shock u_t^G of one standard deviation forecast error of log income.

We calculate inequality as the standard deviation of logs, and for this exercise alone we consider "assets" as cash-on-hand (i.e. financial assets plus current income) so that borrowing constrained households do not have undefined log assets.



(a) Std. Deviation of Log Assets



(b) Std. Deviation of Log Consumption

Figure 5: Inequality Response to Aggregate Shocks

Notes: Impulse response functions are calculated by subjecting the economy to a one standard deviation aggregate income shock, and comparing with a counterfactual economy receiving no shock. The impulse response functions are reported as the percentage point difference in the standard deviation of log consumption or log assets, relative to the counterfactual economy, and normalized by the size of the shock.

Under full information, the standard model predicts that a positive aggregate income shock should reduce consumption and asset inequality (Figure 5, dashed lines). This reduction occurs because all incomes increase proportionately, and income is distributed more equally than assets. To understand this effect, it is useful to view a household's "total wealth" as the sum of financial wealth (i.e. the assets in the model) and human capital (i.e. the present value of future income $Y_{i,t}$) because, absent any financial friction, total wealth would entirely determine consumption. The aggregate shock reduces the share of households' total wealth that is held as financial assets and increases the share held as human capital. As usual, financial assets are distributed more unequally than income, so shifting towards human capital reduces consumption inequality (panel (a)). Similarly, the shift towards human capital causes savings to be distributed more equally, reducing asset inequality (panel (b)).

Under incomplete information, agents have a stronger precautionary savings motive, so they hold more financial assets. Therefore when the aggregate shock increases incomes, it has a smaller effect on the shares of total wealth held as financial assets and human capital. The shock induces a smaller shift towards the more equally distributed human capital than under full information, attenuating the reductions in consumption and asset inequality.

4.2 Forecast Heterogeneity

One implication of heterogeneity among agents is that there is heterogeneity of forecasts. This is true of any model with a persistent income process. But the information friction introduces an additional complication: there is heterogeneity of forecasts *about aggregate variables.*

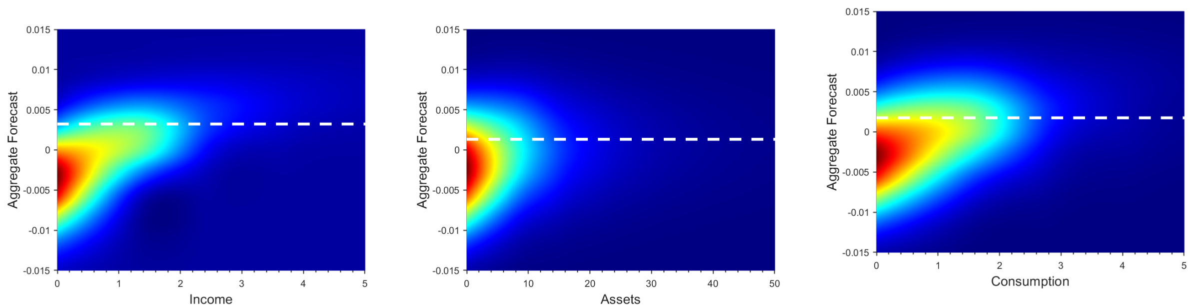
There is clear empirical evidence that households have heterogeneous forecasts about the macroeconomy.[19] This heterogeneity requires information frictions because FIRE agents all form the same expectations. But there is an additional interaction between the friction and the agent heterogeneity: in linear dispersed information models, the average agent typically holds the average expectation, so the heterogeneity of expectations is irrelevant for macroeconomic dynamics. A consequence of the heterogeneous agent framework is that forecasts about aggregates are nonlinearly related to the endogenous distributions of wealth and consumption.

What is the mechanism? Income is persistent, so higher income individuals expect higher income in the future. Because they cannot disentangle idiosyncratic from aggregate incomes, agents that have higher forecasts of their own income also have higher forecasts of aggregate income. This relationship is strictly mechanical, following from the assumed income process.[20] But income is endogenously correlated with wealth and consumption, so forecasts of aggregates are endogenously correlated as well.

Figure 6 plots the joint distributions of household forecasts of aggregate log incomes and other quantities in the incomplete information model. The joint distribution with income is plotted in panel (a): this relationship is mechanical, entirely implied by the assumed income process and information friction. When households receive higher income, they tend to save, so wealth is positively correlated with income and thus the forecast in panel (b). However, households with higher income do not save it all; they also consume, which thus is positively correlated with forecasts in panel (c).

[19] A large literature documents how heterogeneous forecasts about macroeconomic variables are correlated with household decisions, including Vissing-Jorgensen (2003), Egan et al. (2021a), Egan et al. (2021b), Coibion et al. (2021), and Coibion et al. (2022).

[20] Appendix B.5 derives this relationship.



(a) Correlation with Income

(b) Correlation with Assets

(c) Correlation with Consumption

Figure 6: Distributions of Expectations

Notes: The heatmaps display the ergodic joint distributions in the incomplete information model of: (1.) household forecasts of aggregate income and (2.) either income, assets, or consumption. Red regions indicate the highest density, while blue regions indicate the lowest. The dashed white lines mark the average household, weighted by the x-axis quantity.

The joint distributions have three common patterns. First, the forecasts feature substantial heterogeneity. Second, optimism about the aggregate economy is positively correlated with income, wealth, and consumption. Third, the joint distributions are all skewed with respect to the x-axis. This inequality is typical in heterogeneous agent models. But it has a crucial interaction with the information friction: the skewness biases any weighted-average of forecasts. This can be seen in Figure 6, where the dashed white lines plot the average forecast, weighted by the corresponding x-axis variable. In all cases, this weighted average is greater than the unweighted average, which is necessarily zero.

Our model is simple, but we expect these patterns hold in more general settings so long as income is sufficiently correlated with wealth and consumption. In other models, the consequences of these patterns depend on what matters for the macroeconomy: for example, if it is the forecast associated with the average asset (rather than the average household) that matters for the macroeconomy, then this unequal joint distribution can further distort aggregate dynamics.

5 Corroborating Evidence for the Mechanism

In this section we examine whether household expectations of their future earnings respond differently to idiosyncratic and aggregate shocks. If households have full information, then their expectations should respond more elastically to idiosyncratic earnings, because the idiosyncratic component is more persistent than the aggregate component. We test this prediction using survey data and find the opposite: household expectations are at least as elastic to aggregate earnings. This supports the central mechanism in our model.

5.1 Data

To document the response of household earnings forecasts to idiosyncratic and aggregate shocks, we employ data from the New York Fed Survey of Consumer Expectations (SCE). The SCE is a monthly survey of aggregate and household-level economic conditions and forecasts. It consists of a nationally representative rotating panel of approximately 1300 American households, which remain in the sample for up to 12 months. The survey has been administered since 2013. For our purposes, we require data on both expected and realized household earnings. Unfortunately, this pair is reported only in the auxiliary labor market module of the survey, which is administered to participants every 4 months.

We primarily use two questions from the labor market module. First, to measure household expectations of future earnings, we use the household head's forecast of their 4-month-ahead earnings. This measure is the answer to:

> *What do you believe your annual earnings will be in 4 months?*
> ____*dollars per year*

which we interpret as the household's forecast of instantaneous annualized earnings four months into the future. The advantage of this measure relative to the earnings forecasts in the general SCE survey, is that it is unconditional. The general SCE asks respondents to forecast their earnings over the following year, but do so conditional on holding a job. We prefer to use an unconditional earnings process, which both fits the model and corresponds to the process that we estimate in the aggregate.

Second, to measure realized income, we use the household head's current annualized reported earnings. This measure is the answer to:

> *How much do you make **before** taxes and other deductions at your [main/current] job, on an annual basis? Please include any bonuses, overtime pay, tips or commissions.*
> ____*dollars per year*

measured as gross wages or salaries, which respondents are more likely to report accurately. This question is not asked to individuals who are unemployed or out of the labor force, to whom we assign zero earnings. The earnings expectation question was added only in March 2015, and the last wave in our data set is July 2021, giving us 20 time periods. The data set contains 11,930 unique households, appearing on average in 2.5 editions of the module. But not all respondents answer all questions; we are left with 14,378 observations with sufficient data.

The general SCE survey contains additional household-level descriptors. Crucially, we observe the state where respondents reside, so that we can connect households to state-level shocks. We use additional descriptors as controls: we observe the industry in which the head of household either works or was employed most recently, we observe their age and education, and we observe demographic characteristics including ethnicity and gender.

5.2 Regressions

We divide a household's log real detrended labor earnings $y_{i,s,t}$ into an idiosyncratic component $y^{Idio}_{i,s,t}$ and an aggregate component $y^{Aggr}_{s,t}$:

$$y_{i,s,t} = y^{Idio}_{i,s,t} + y^{Aggr}_{s,t}$$

where i indexes households, s indexes their state, and t indexes the 4 month time period. The aggregate component $y^{Aggr}_{s,t}$ is the mean earnings in state s and period t as reported in the national accounts. We aggregate at the state level for several reasons. First, using states rather than the entire US economy provides considerably more observations, which is essential given the short history of the SCE. Second, state-level income is more volatile than aggregate income, which gives our analysis additional power. Finally, we treat states as small open economies, which matches the structure of our model and the motivating evidence from Guntin et al. (2023).

Our main regression estimates how household forecasts depend on earnings:

$$f^{y}_{i,s,t} = \beta^{Idio} y^{Idio}_{i,s,t} + \beta^{Aggr} y^{Aggr}_{s,t} + X_{i,s,t} + \varepsilon_{i,s,t} \tag{7}$$

where i indexes households, s indexes their state, and t indexes the 4 month time period. $f^{y}_{i,s,t}$ is the household-level forecast of their 4-month-ahead earnings, $y^{Idio}_{i,s,t}$ and $y^{Aggr}_{s,t}$ are the realized aggregate and idiosyncratic earnings components, $X_{i,s,t}$ is a vector of household-level controls, and $\varepsilon_{i,s,t}$ is an orthogonal residual.

This is a useful regression because it can directly test whether households' forecasts respond to income changes in the way that is consistent with FIRE. Proposition 1 formalizes this feature. When proving this result, we can relax the assumption that the income components $y^{Idio}_{i,s,t}$ and $y^{Aggr}_{s,t}$ are AR(1). Instead, we only assume that these components are stationary ARMA processes with Gaussian innovations $u^{Idio}_{i,s,t}$ and $u^{Aggr}_{s,t}$. Write these processes in $AR(\infty)$ form as:

$$y_{i,s,t}^{Idio} = \sum_{k=1}^{\infty} \rho_k^{Idio} y_{i,s,t-k}^{Idio} + u_{i,s,t}^{Idio} \qquad\qquad y_{i,s,t}^{Aggr} = \sum_{k=1}^{\infty} \rho_k^{Aggr} y_{i,s,t-k}^{Aggr} + u_{s,t}^{Aggr} \tag{8}$$

The innovations $u_{i,s,t}^{Idio}$ and $u_{s,t}^{Aggr}$ are orthogonal to past income components, but may be predicted by other information available to households.

Proposition 1 *If households have full information and rational expectations, then the coefficients in equation* (7) *will satisfy*

$$\beta^{Idio} = \rho_1^{Idio} \qquad\qquad \beta^{Aggr} = \rho_1^{Aggr}$$

if the vector $X_{i,s,t}$ *contains the remaining relevant income lags.*

Proof: See Appendix G.

Crucially, Proposition 1 holds whether or not households have additional news about future income that is not observable to the econometrician. They may anticipate future innovations, but such information does not need to be controlled for when estimating regression (7). Intuitively, future income innovations are orthogonal to current income components, so this must also be true for the forecasts of FIRE households.

In the model, the earnings components are both AR(1). And if the components $y_{i,s,t}^{Idio}$ and $y_{s,t}^{Aggr}$ are each AR(1) with autocorrelation ρ^{Idio} and ρ^{Aggr} respectively, then the forecast (7) under full information would satisfy

$$\text{[FIRE, AR(1)]:} \qquad \beta^{Idio} = \rho^{Idio} \qquad \beta^{Aggr} = \rho^{Aggr} \tag{9}$$

However, if households are unable to distinguish between aggregate and idiosyncratic earnings components, then the forecast (7) would satisfy

$$\text{[Incomplete Info., AR(1)]:} \qquad \beta^{Idio} = \beta^{Aggr} \tag{10}$$

We test these information structures when estimating regression (7). Our calibrated parameters $\rho^{Idio} = 0.97$ and $\rho^{Aggr} = 0.87$ imply that if FIRE holds, then we should expect $\beta^{Idio} > \beta^{Aggr}$. Yet even though incomplete information implies $\beta^{Idio} = \beta^{Aggr}$, our main approach is not to test this equality, because failing to reject the null hypothesis is not a confirmation of information frictions. Moreover, if the equality fails to hold, we care whether it fails in the direction implied by full information, or whether it fails in the direction that reinforces our model's mechanism. Therefore, we perform a one-sided test with the alternative hypothesis that β^{Aggr} is *larger* than β^{Idio}. If we reject the null hypothesis that $\beta^{Idio} \geq \beta^{Aggr}$, then we conclude that FIRE fails in the direction that supports our model.

5.3 Results

Table 4 presents the results of forecast regression (7). Column (1) is the basic regression with no additional controls. In column (2), we control for state-level effects on expectations. We cannot include state-time controls, because aggregate earnings vary at the state level. Column (3) includes additional worker-specific for industry, education, age, gender, and race. In column (4) we further account for additional information available to households by controlling for their lagged earnings; this is our preferred specification. Column (5) also controls for lagged forecasts, which reduces the number of observations. Column (6) includes lagged idiosyncratic and aggregate earnings separately even though our theory assumes that households cannot distinguish between these two components. In column (7) we define idiosyncratic and aggregate components using national instead of state-level earnings. And finally in column (8), we instrument for $y^{Idio}_{i,s,t}$ with $y^{Idio}_{i,s,t-1}$ in order to avoid bias induced by transitory measurement error in households' reported earnings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Idio. Log Earnings	0.668	0.666	0.619	0.545	0.484	0.545	0.545	0.940
	(0.0177)	(0.0178)	(0.0204)	(0.0377)	(0.0427)	(0.0377)	(0.0376)	(0.0311)
Aggr. Log Earnings	1.313	1.539	1.357	1.129	0.934	1.786	2.112	1.982
	(0.192)	(0.265)	(0.256)	(0.355)	(0.377)	(0.696)	(0.539)	(0.408)
Lag Log Earnings				0.204	0.101		0.203	
				(0.0271)	(0.0278)		(0.0270)	
Lag Forecast					0.218			
					(0.0318)			
Lag Idio. Log Earnings						0.204		
						(0.0271)		
Lag Aggr. Earnings						-0.556		
						(0.756)		
H_0: $\beta^{Idio} \geq \beta^{Aggr}$ p-value	0.000	0.001	0.002	0.047	0.110	0.036	0.002	0.005
Observations	14378	14378	14364	7469	7087	7469	7469	7469
R^2	0.524	0.527	0.544	0.621	0.631	0.622	0.622	0.508
State F.E.		X	X	X	X	X	X	X
Household Controls			X	X	X	X	X	X
Aggregation Level	State	State	State	State	State	State	USA	State
Regression Type	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV

Notes: Standard errors in parentheses, clustered at the state-month level. In all cases, the dependent variable is the household-level log forecast of its 4-month-ahead annualized earnings. The reported p-value is from a one-sided test with H_A: $\beta^{Idio} < \beta^{Aggr}$. In the IV regression, idiosyncratic income is instrumented for by its one period lag.

Table 4: Effects of Log Earnings on Household Earnings Forecasts

In all cases, the coefficient on aggregate log earnings exceeds that of idiosyncratic log earnings. Household forecasts of future earnings are more sensitive to changes in aggregate earnings, even though their idiosyncratic earnings are much more persistent! The test results formalize this conclusion. When we test the null hypothesis that $\beta^{Idio} > \beta^{Aggr}$, as implied by full information, we reject the inequality at the 5% level in our preferred specification (4). This means that the relative response of household forecasts to aggregate earnings exceeds what it would be under full information, or if full information failed but in the opposite direction than implied by our model. And even in specification (5) when our statistical test fails to reject, our estimates remain a better fit to the incomplete information model than the full information model.

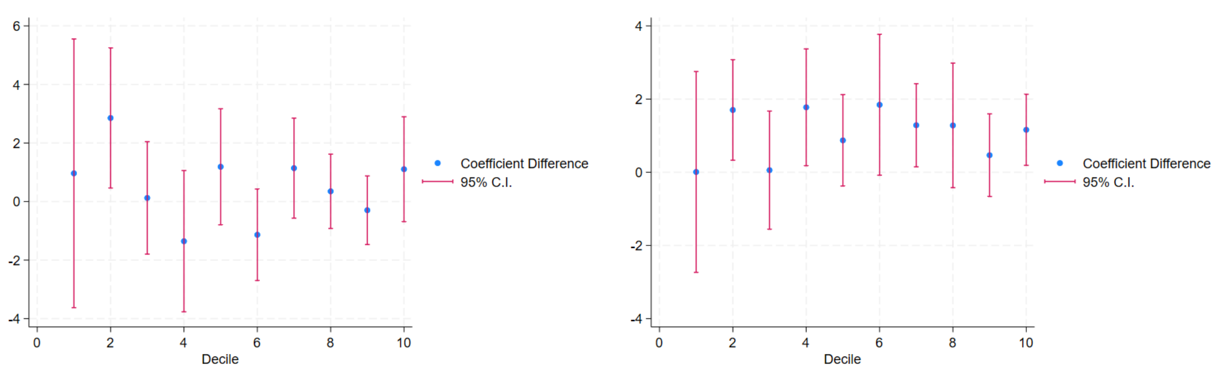
Our results validate the model's mechanism: household forecasts are *not* more elastic to idiosyncratic earnings. The forecast regressions in this section are the clearest test of the information friction, but we run additional tests in Appendix E, where we estimate that households have predictable forecast errors that overreact to aggregate earnings, and we learn that household consumption is also more elastic to aggregate than idiosyncratic earnings.

These tests lean on average responses of household expectations to aggregate shocks. But could households respond heterogeneously across the income distribution? We explore this question in the next section.

5.4 Expectation Elasticity Homogeneity

The main consequence of the information friction in our model is that agents' income expectations are not more elastic to idiosyncratic shocks than to aggregate shocks. In both our model and main empirical tests, we assume that the response of expectations to income shocks are homogeneous across the income distribution. To establish whether this is a reasonable assumption, we run two types of tests for heterogeneity by income.

First, we examine how the response of expectations to log income varies by income decile. Specifically, we separate households into log income deciles in each time period $t-1$, then run our main regression (7) for time period t separately for each decile. Figure 7 reports the difference $\beta^{Aggr} - \beta^{Idio}$ between the estimated coefficients, and the 95% confidence intervals associated with this difference. Panel (a) includes lagged log income as a control, corresponding to the preferred specification in our main analysis (column (4) in Table 4); panel (b) reports the simplest specification of forecasts on aggregate and idiosyncratic income without any additional controls (corresponding to column (1) in Table 4). In both cases, there is no obvious relationship between income level and the difference in how household expectations respond to aggregate vs. idiosyncratic income. And for all deciles, the difference is either statistically indifferent from zero, or households are more elastic to aggregate income.



(a) Fixed Effect Specification With Lag Income

(b) Simple Specification

Figure 7: Estimated Coefficient Differences by Income Decile

Notes: The figure reports how the response of expectations to aggregate and idiosyncratic income vary by income decile. Each panel plots the difference in estimated coefficients $\beta^{Aggr} - \beta^{Idio}$ from regression (7) by income decile, and the associated 95% confidence intervals. Panel (a) controls for household fixed effects and lag income, as in column (4) of Table 4. Panel (b) includes no additional controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Idio. Log Earnings	0.581	0.573	0.568	0.495	0.414	0.495	0.495
	(0.0409)	(0.0409)	(0.0422)	(0.0472)	(0.0481)	(0.0472)	(0.0470)
Aggr. Log Earnings	1.197	1.494	1.391	1.163	0.977	1.756	2.281
	(0.585)	(0.614)	(0.611)	(0.725)	(0.738)	(0.913)	(0.560)
Idio. Log Earnings × Lag Percentile	-0.000621	-0.000719	-0.000753	0.000198	0.00117	0.000198	0.000195
	(0.000898)	(0.000921)	(0.000960)	(0.000999)	(0.00102)	(0.000998)	(0.000996)
Aggr. Log Earnings × Lag Percentile	0.00618	0.00127	0.000962	-0.000153	0.000462	-0.000106	-0.0000377
	(0.00846)	(0.00874)	(0.00872)	(0.0105)	(0.0105)	(0.0105)	(0.00258)
Lag Forecast					0.193		
					(0.0306)		
Lag Idio. Log Earnings						0.0977	
						(0.0319)	
Lag Aggr. Earnings						-0.590	
						(0.739)	
$\gamma^{Aggr} - \gamma^{Idio}$ estimate	0.007	0.002	0.002	-0.000	-0.001	-0.000	-0.000
$\gamma^{Aggr} = \gamma^{Idio}$ p-value	0.437	0.825	0.849	0.974	0.948	0.978	0.926
Observations	7861	7861	7855	7469	7087	7469	7469
R^2	0.611	0.617	0.620	0.632	0.639	0.632	0.632
State F.E.		X	X	X	X	X	X
Household Controls			X	X	X	X	X
Aggregation Level	State	State	State	State	State	State	USA

Notes: Standard errors in parentheses, clustered at the state-month level. In all cases, the dependent variable is the household-level log forecast of its 4-month-ahead annualized earnings.

Table 5: Income Dependence in Effects of Log Earnings on Household Earnings Forecasts

Second, we directly test whether a household's position in the income distribution affects its response of expectations to income. We estimate the following regression that includes interactions between a household's lagged income percentile and its current aggregate and idiosyncratic income components:

$$f^y_{i,s,t} = \beta^{Idio} y^{Idio}_{i,s,t} + \beta^{Aggr} y^{Aggr}_{s,t} + \beta^{Lag} p_{i,s,t-1} + \gamma^{Idio} y^{Idio}_{i,s,t} \times p_{i,s,t-1} + \gamma^{Aggr} y^{Aggr}_{s,t} \times p_{i,s,t-1} + X_{i,s,t} + \varepsilon_{i,s,t} \tag{11}$$

where $p_{i,s,t-1}$ denotes the percentile of household i's earnings in the time $t-1$ income distribution. The remaining variables are unchanged from the main regressions in Section 5.2.

Then in order to evaluate how a household's income level affects the relative response of expectations to income components, we test whether $\gamma^{Aggr} - \gamma^{Idio}$ is different from zero. Table 5 reports the results. Column (1) includes no additional controls, column (2) adds state fixed effects, and column (3) adds the remaining household dummies. Column (4) controls for additional household information by including their lagged forecast, and column (5) controls for even more information by including the lagged aggregate and idiosyncratic earnings components. In column (6), the aggregate component is calculated at the national level instead of by state.

In every case, the effect of income on the relative response to aggregate vs idiosyncratic income is not significantly different from zero, in either a statistical or economic sense. Consider the largest magnitude estimate: $\gamma^{Aggr} - \gamma^{Idio} = 0.007$ implies that if household rise in the income distribution by 10 percentiles, the difference between the elasticity to aggregate and idiosyncratic components changes by only 0.07.

In this section, we learned that the behavior of household forecasts across the income distribution is unlikely to feature heterogeneity that would affect our main conclusions. However, households can still feature forecasting heterogeneity in the data. Is their heterogeneity consistent with our model's mechanisms? We explore this question next.

5.5 Absolute Forecast Error Tests

In the Section 2 model, all households face the same process for information, and have rational expectations, so all households are equally good forecasters. But an implication of the information friction is that if some households *did* have better information about the macroeconomy than others, they would be better forecasters of their own income. For example, this is why the information friction is less impactful in the unemployment model (Section 3.3).

To test this implication, we run the following regression:

$$|y_{i,s,m+4} - f^{y}_{i,s,m}| = \sum_{j=0}^{J} \beta_j |\pi_{m+12-j} - f^{\pi}_{i,s,m-j}| + X_{i,s,m} + \varepsilon_{i,s,m} \tag{12}$$

On the left-hand side is the absolute forecast error for log earnings made by household i in state s and month m. We denote the time period by m to distinguish it from the 4-monthly time period used in our main tests. On the right-hand side are lags of $|\pi_{m+12-j} - f^{\pi}_{i,s,m-j}|$, the household's absolute forecast error for 12-month-ahead inflation. Earnings forecasts are only collected by the SCE every four months, but the inflation forecasts are collected monthly, allowing us to introduce a number of lags of the absolute inflation forecast error without substantially reducing the sample size.

Table 6 presents our estimates of equation (12). Columns (1-3) add lags of the absolute inflation errors. Column (4) adds state fixed effects, and column (5) adds the lagged absolute earning forecast error.

	(1)	(2)	(3)	(4)	(5)
Absolute Inflation Error	0.015	0.012	0.0075	0.0077	0.0064
	(0.0024)	(0.0033)	(0.0042)	(0.0042)	(0.0041)
1 Month Lag		0.0055	0.0062	0.0061	0.0052
		(0.0024)	(0.0032)	(0.0032)	(0.0031)
2 Month Lags			0.0071	0.0072	0.0055
			(0.0027)	(0.0027)	(0.0026)
Observations	7435	7010	5642	5642	5639
R^2	0.023	0.025	0.031	0.041	0.061
State F.E.				X	X
Household Controls					X

Notes: Standard errors in parentheses, clustered at the state-month level. Household controls include human capital, demographic, and age fixed effects. In all cases, the dependent variable is the magnitude of the household forecast error of log earnings.

Table 6: Earnings and Inflation Co-forecastability

Across specifications, we find that households that make more accurate inflation forecasts also make more accurate forecasts of their own earnings. When adding controls for household characteristics, the coefficients on absolute inflation forecast errors are slightly reduced, indicating that only some of a household's superior forecasting ability is correlated with its observable characteristics. Our findings support the information friction in our model: a contributor to poor household earnings forecasting is poor information about the macroeconomy.

6 Conclusion

In this paper we introduced dispersed information to an otherwise standard open economy heterogeneous agents model. We demonstrated that the information friction increased consumption volatility and reduced heterogeneity in household's response to aggregate income shocks. Then we documented evidence for our central mechanism in US forecast data.

Our central findings are robust, but there is further work to be done. How would the friction interact with capital accumulation in the model? Or a richer asset market or household risks and decisions? What about closed economies? Regardless, it is clear that households respond to aggregate shocks as if they are more persistent than they actually are, so this type of information friction will be valuable in any setting where consumption volatility matters.

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Appendix

A Aggregate Income Persistence

In this section we estimate the autocorrelation of aggregate log labor earnings.

We measure average log real labor earnings $y_{s,t}^{Aggr}$ at the state level from the National Accounts, for state s and year t. We define labor earnings as the sum of wages and salaries, supplements to wages and salaries, and proprietors' income. We deflate by the PCE deflator, to match the procedure used by Guvenen et al. (2021) for idiosyncratic earnings. We estimate the following panel regression:

$$y_{s,t}^{Aggr} = \rho^{Aggr} y_{s,t-1}^{Aggr} + d_s + X_{s,t} + \varepsilon_{s,t}$$

where d_s denote fixed state-level controls, while $X_{s,t}$ are further controls that vary with time. We estimate this regression both by OLS and by 2SLS, instrumenting for $y_{s,t-1}^{Aggr}$ with $y_{s,t-2}^{Aggr}$. The IV regressions allows for consistent estimation of ρ^{Aggr} even when the error term $\varepsilon_{i,s,t}$ is MA(1). We take this approach in order to be comparable to Guvenen et al. (2021), who allow individual earnings to contain an i.i.d. transitory term, which is equivalent to letting earnings be ARMA(1,1).

Table 7 reports our estimates of ρ^{Aggr}. Columns (1) report results for the regression with state-specific as the only controls, which allows for the longest sample. We let our trends be state-specific, given the well-known heterogeneity of growth rates across states (Barro et al., 1991). This is our simplest specification and yields the largest estimate, but even in this case it is significantly lower than the idiosyncratic persistence. In specifications (2) and (3) we control for state-level demographics, as changes in worker composition affect average earnings in a predictable way. We include data from the Current Population Survey on age, gender, race, and education. Controlling for these factors, we estimate an autocorrelation of 0.89 or 0.87 depending on whether our controls are additive or interacted with a time trend, respectively. The specifications (4)-(5) use the 2SLS approach in order to allow for transitory i.i.d. shocks to earnings or measurement error. Allowing for these transitory shocks reduces the estimated magnitudes even further: 0.84 and 0.82 respectively. Next, we run our estimation for the 1994-2013 subsample, in order to most directly compare our aggregate estimate with the idiosyncratic autocorrelation estimated from this sample period by Guvenen et al. (2021), which is the value for ρ^{Idio} that we use in our calibration. Columns (6) and (7) present these results, with autocorrelations of 0.80 or 0.59; during this time period, income was generally less persistent than in the broader sample. Lastly, columns (8) and (9) reproduce specifications (3) and (5), except normalizing earnings by employment instead of by population: the coefficients are similar.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag Real Earnings	0.926	0.885	0.871	0.836	0.815	0.801	0.558	0.856	0.830
	(0.006)	(0.008)	(0.008)	(0.009)	(0.009)	(0.017)	(0.030)	(0.010)	(0.011)
Observations	4701	2737	2737	2737	2737	1020	1020	2404	2385
R^2	0.991	0.995	0.995	0.995	0.995	0.992	0.993	0.990	0.990
State Trends	X	X	X	X	X	X	X	X	X
Demo. F.E.		X		X		X			
Demo. Trends			X		X		X	X	X
Transitory Shocks				X	X	X	X		X
Earnings Per:	Pop.	Pop.	Pop.	Pop.	Pop.	Pop.	Pop.	Emp.	Emp.
Sample Period	1929-2022	1962-2022	1962-2022	1962-2022	1962-2022	1994-2013	1994-2013	1962-2022	1962-2022

Notes: Heteroskedasticity-consistent standard errors in parentheses. In all cases the dependent variable is state-level average annual labor earnings.

Table 7: Aggregate Earnings Autocorrelations

Our preferred specification is column (5), given that we expect the effects of demographic factors on income to change over time, due to female entry into the labor force, changing attitudes towards race, and rising capital-skill complementarity (Krusell et al., 2000). However, we choose specification (3)'s 0.87 as our baseline calibration for ρ^{Aggr}; smaller values will strengthen the effects of the information friction in our model, and we aim to be conservative in our approach. It might be reasonable to choose a lower value, given the lower estimates for the 1994-2013 time period that informs our idiosyncratic process. But, we are concerned that this shorter time period might be susceptible to Nickell bias attenuating the estimates, so we are wary of selecting the lowest estimates.

B The Sum of Independent Income Processes

In this appendix, we characterize the time series properties of log income in the model. Index households by i and time by t. Household log income $y_{i,t}$ is given by

$$y_{i,t} = ay^I_{i,t} + by^G_t$$

where $y^I_{i,t}$ is idiosyncratic and mean zero in the population for all t, while y^G_t is aggregate and common to all households. $a \geq 0$ and $b \geq 0$ represent the relative weights of the idiosyncratic and aggregate components on household income. Note that in our baseline scenario we have $a = b = 1$.

B.1 The ARMA(2,1) Representation

The idiosyncratic and aggregate components are AR(1):

$$y^I_{i,t} = \rho_I y^I_{i,t-1} + u^I_{i,t}$$

$$y^G_{i,t} = \rho_G y^G_{i,t-1} + u^G_{i,t}$$

with $u^I_{i,t} \sim N(0, \sigma^2_I)$, $u^G_t \sim N(0, \sigma^2_G)$, $\rho_I \in (0,1)$, and $\rho_G \in (0,1)$.

It is helpful to use lag operator notation to define these time series, which become:

$$y^I = L\rho_I y^I + u^I$$

$$y^G = L\rho_G y^G + u^G$$

$$y = L\varrho(L)y + w$$

where ϱ is a lag operator polynomial to be found, and w is a white noise process to be found.

It is well known that the sum of AR(1) processes is ARMA(2,1). The autoregressive coefficients parameters are $\varrho_0 = \rho_I + \rho_G$ and $\varrho_1 = -\rho_I\rho_G$:

$$y - (\rho_I + \rho_G)Ly + \rho_I\rho_G L^2 y = ay_I + by_G - (\rho_I + \rho_G)L(ay_I + by_G) + \rho_I\rho_G L^2(ay_I + by_G)$$

$$= a\rho_I Ly_I + au_I + b\rho_G Ly_G + bu_G - (\rho_I + \rho_G)L(ay_I + by_G) + \rho_I\rho_G L^2(ay_I + by_G)$$

$$= au_I + bu_G - a\rho_G Ly_I - b\rho_I Ly_G + \rho_I\rho_G L^2(ay_I + by_G)$$

$$= au_I + bu_G - a\rho_G L(y_I - \rho_I Ly_I) - b\rho_I L(y_G - \rho_G Ly_G)$$

$$= au_I + bu_G - a\rho_G Lu_I - b\rho_I Lu_G \equiv z$$

The object z is $MA(1)$. What is the structure of the MA term? To answer this, note that

$$\mathrm{Cov}(z, L^j z) = \begin{cases} a^2\mathrm{Var}(u_I)(1+\rho_G^2) + b^2\mathrm{Var}(u_G)(1+\rho_I^2) & j = 0 \\ -a^2\mathrm{Var}(u_I)\rho_G - b^2\mathrm{Var}(u_G)\rho_I & j = 1 \\ 0 & j > 1 \end{cases}$$

thus we can write

$$z = w + \theta Lw$$

To finish characterizing the ARMA process, we need to know the variance of w, and the value of θ. These quantities are related by two equations:

$$\mathrm{Var}(z) = \mathrm{Var}(w) + \theta^2\mathrm{Var}(w)$$

$$\mathrm{Cov}(z, Lz) = \theta\mathrm{Var}(w)$$

which imply

$$0 = \mathrm{Var}(w)^2 - \mathrm{Var}(z)\mathrm{Var}(w) + \mathrm{Cov}(z, Lz)^2$$

Apply the quadratic formula and take the larger root:

$$\text{Var}(w) = \frac{\text{Var}(z)}{2} + \sqrt{\left(\frac{\text{Var}(z)}{2}\right)^2 - \text{Cov}(z, Lz)^2}$$

Then calculate θ by

$$\theta = \text{Cov}(z, Lz)/\text{Var}(w)$$

Finally, w can be expressed analytically in terms of the underlying shocks:

$$w = (1 + \theta L)^{-1} z = z - \theta Lz + \theta^2 L^2 z - ...$$

$$w = (1 + \theta L)^{-1}(I - \rho_G L)au_I + (1 + \theta L)^{-1}(I - \rho_I L)bu_G \tag{13}$$

Altogether, the ARMA(2,1) representation is

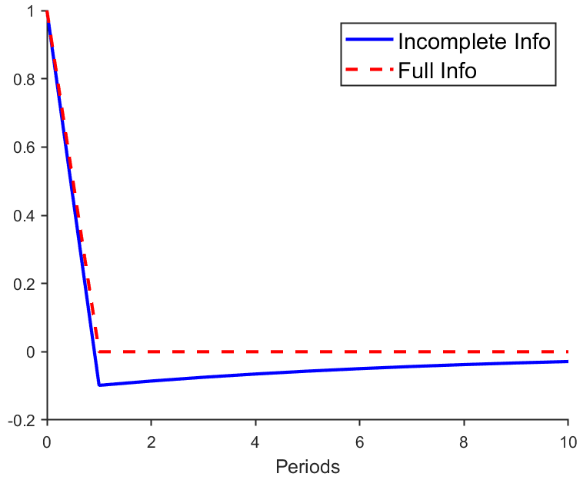
$$y_{i,t} = \varrho_0 y_{i,t-1} + \varrho_1 y_{i,t-2} + w_{i,t} + \theta w_{i,t-1} \tag{14}$$

B.2 The Effects of Shocks on Forecast Errors

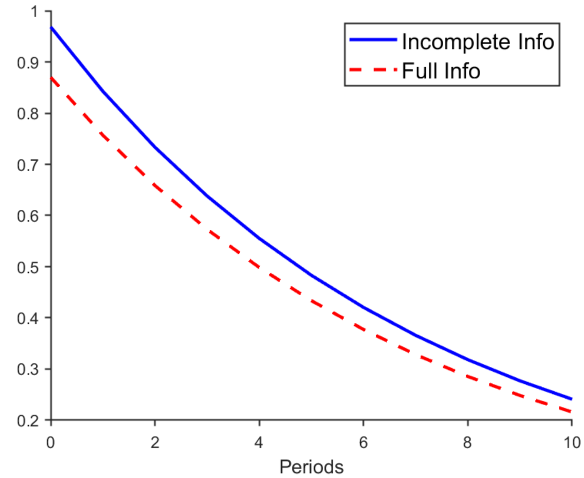
How do shocks affect forecast errors? Equation (13) provides the answer, by writing the household forecast error w_t in terms of past aggregate and idiosyncratic shocks. Figure 8 represents this dynamic relationship by plotting the impulse response of forecast errors and one-period-ahead forecasts to a unit aggregate shock.

Under full information, households make an immediate forecast error (panel (a)), but all future effects of the aggregate shock are predictable, so the impulse response function is zero thereafter. In panel (b), the full information forecast follows the true income IRF, shifted one period ahead.

Under incomplete information, households make the same immediate forecast error (panel (a)). But the aggregate affects future forecast errors as well. In every following period, the forecast error is negative; households are repeatedly surprised that their incomes decayed



(a) Forecast Errors



(b) One-Period-Ahead Forecasts

Figure 8: Impulse Responses to an Aggregate Income Shock

Notes: The figures plot the impulse response of income forecast errors and one-period-ahead forecasts to a unit aggregate shock in the baseline model. The solid blue line is the response under incomplete information. The dashed red line is the response under full information. The impulse response functions are calculated using the baseline calibration.

faster than they had predicted. This is because households think it is likely that their income improvement was due to an idiosyncratic shock, which decays more slowly. Thus their one-period-ahead forecast is perpetually above the full information forecast (panel (b)).

B.3 The VAR(1) Representation

Stack the variables as such:

$$\boldsymbol{y}_{i,t} \equiv \begin{pmatrix} y_{i,t} \\ y_{i,t-1} \\ w_{i,t} \end{pmatrix}$$

Then $\boldsymbol{y}_{i,t}$ is a VAR(1) with coefficient matrix $B = \begin{pmatrix} \varrho_0 & \varrho_1 & \theta \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$ and innovation $Cw_{i,t}$ for $C = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$:

$$\boldsymbol{y}_t = B\boldsymbol{y}_{i,t-1} + Cw_{i,t}$$

B.4 Income Forecasts at Various Horizons

This section derives the term structure of expectations under the information friction, which are is used in Section 2.2.

Income follows the ARMA(2,1) process

$$y_{i,t} = \varrho_0 y_{i,t-1} + \varrho_1 y_{i,t-2} + w_{i,t} + \theta w_{i,t-1}$$

so the one-period-ahead forecast is given by

$$\mathbb{E}[y_{i,t+1}|\Omega_{i,t}] = \varrho_0 y_{i,t} + \varrho_1 y_{i,t-1} + \theta w_{i,t}$$

because $\mathbb{E}[w_{i,t+1}|\Omega_{i,t}] = 0$.

The two-period-ahead forecast is given by

$$\mathbb{E}[y_{i,t+2}|\Omega_{i,t}] = \varrho_0 \mathbb{E}[y_{i,t+1}|\Omega_{i,t}] + \varrho_1 y_{i,t}$$

beyond this horizon, the h-period-ahead forecast can be found recursively by

$$\mathbb{E}[y_{i,t+h}|\Omega_{i,t}] = \varrho_0 \mathbb{E}[y_{i,t+h-1}|\Omega_{i,t}] + \varrho_1 \mathbb{E}[y_{i,t+h-2}|\Omega_{i,t}]$$

for $h \geq 2$.

B.5 Forecasts of Aggregate Income

In the model, agents have no need to forecast the aggregate economy; they only need to forecast their own income. However, it is possible to construct the forecasts that agents would make, given the information friction that they face.

Agent i's forecast of aggregate income conditional on their information set $\Omega_{i,t}$ is

$$\mathbb{E}[y^G_{t+1}|\Omega_{i,t}] = \rho_G \mathbb{E}[y^G_t|\Omega_{i,t}]$$

$$= \rho^G \sum_{j=0}^{\infty} \rho_G^j \mathbb{E}[u^G_{t-j}|\Omega_{i,t}]$$

How do agents form expectations over past shocks? Linear backcasting is easily expressed in terms of current and past orthogonal forecast errors $w_{i,t}$. Let W^G denote the lag operator polynomial that gives the aggregate component of $w_{i,t}$ from current and past aggregate shocks. Per equation (13), this polynomial is given by $W^G(L) = \frac{1-\rho_I L}{1+\theta L}$. Let W^G_j denote the j coefficient of this polynomial. Then the backcast is given by:

$$\begin{aligned}\mathbb{E}[u^G_{t-j}|\Omega_{i,t}] &= \sum_{k=0}^{j} \frac{\text{Cov}(u^G_{t-j}, w_{i,t-k})}{var(w_{i,t-k})} w_{i,t-k} \\ &= \sum_{k=0}^{j} \frac{\text{Cov}(u^G_{t-j}, W^G_{j-k} u^G_{t-j})}{\text{Var}(w_{i,t-k})} w_{i,t-k} = \frac{\sigma^2_G}{\text{Var}(w_{i,t})} \sum_{k=0}^{j} W^G_{j-k} w_{i,t-k} \quad (15)\end{aligned}$$

Plugging in this backcasting formula gives the expression for the aggregate income forecast:

$$E[y^G_{t+1}|\Omega_{i,t}] = \frac{\rho^G \sigma^2_G}{\text{Var}(w_{i,t})} \sum_{j=0}^{\infty} \sum_{k=0}^{j} \rho_G^j W^G_{j-k} w_{i,t-k}$$

B.6 Limiting Backcasts of Shocks

Households are never able to learn the realizations of their income components Y_t^G or $Y_{i,t}^I$. This is because every period, the household fewer new signals than the number of new shocks that affect them. To see the consequences algebraically, consider the jth backcast of the aggregate shock $bc_{i,t}^j \equiv \mathbb{E}[u_{t-j}^G|\Omega_{i,t}]$. $w_{i,t}$ is white noise, so per equation (15), the variance is

$$\text{Var}(bc_{i,t}^j) = \left(\frac{\sigma_G^2}{\text{Var}(w_{i,t})}\right)^2 \left(\sum_{k=0}^{j}(W_{j-k}^G)^2\text{Var}(w_{i,t})\right)$$

The most accurate backcast is in the limit as $j \to \infty$:

$$\text{Var}(bc_{i,t}^j) \leq \text{Var}(bc_{i,t}^\infty) = \left(\frac{\sigma_G^2}{\text{Var}(w_{i,t})}\right)^2 \left(\sum_{j=0}^{\infty}(W_j^G)^2\text{Var}(w_{i,t})\right)$$

Let W_j^I denote the jth coefficient in the polynomial $W^I(L) \equiv \frac{1-\rho_G L}{1+\theta L}$:

$$= \sigma_G^2 \left(\frac{\sum_{j=0}^{\infty}(W_j^G)^2\sigma_G^2}{\text{Var}(w_{i,t})}\right) = \sigma_G^2 \left(\frac{\sum_{j=0}^{\infty}(W_j^G)^2\sigma_G^2}{\sum_{j=0}^{\infty}(W_j^I)^2\sigma_I^2 + \sum_{j=0}^{\infty}(W_j^G)^2\sigma_G^2}\right) < \sigma_G^2$$

The variance of the backcast of u_t^G is necessarily less than the variance of u_t^G at all horizons. Therefore households never learn u_t^G, which implies they never learn Y_t^G nor $Y_{i,t}^I$.

C Quantitative Appendix: Baseline Model

In this section we provide a description of the method we employ to solve our model and compute impulse response functions, under full and incomplete information. Additionally, we present an analysis of the differences between consumption-income elasticities that arise between the two information structures.

C.1 Solution Method

This section provides a description of the algorithm we use to numerically solve for the equilibrium of the full and incomplete information cases.

We start by discretizing the income processes using the approach of Tauchen (1986). For the full information case we discretize the aggregate and idiosyncratic processes separately (we consider 11 points for each income process). For the incomplete information case we write the income process as a VAR(1) (see B.3 for more details) and then discretize it. Note that the VAR(1) case contains three variables. We allow for 11 points for each variable, so the number of exogenous states is $11 \times 11 \times 11 = 1131$. The asset grid is discrete and consists of 250 points.[21] We skew the allocation of points in the asset grid in order to have a better coverage over lower asset levels.

After discretizing the income processes, we proceed to our time iteration method, which is similar to the one described in Coleman (1990). We start with a conjecture for the asset holdings policy function, A', defined over the state space (Y, A), where Y represents the vector of exogenous states of each model.[22] The steps of the solution algorithm are the following:

1. Start iteration j with a guess for $A'_j(Y, A) \geq -\bar{A}$, where $-\bar{A}$ denotes the borrowing limit. Using this guess construct:

$$C_j(Y, A) = Y + A(1 + r) - A'_j(Y, A) \tag{16}$$

Using (16), compute the discounted expected marginal utility

$$\beta(1 + r^*)\mathbb{E}_{Y'|Y}\left[u_j(Y', A'_j(Y, A))\right], \tag{17}$$

[21] Our results do not change substantially by increasing the number of asset grid points, as our solution method relies on first order conditions.

[22] Note that this guess corresponds to a matrix with dimensions $N_Y \times N_A$, where N_Y and N_A correspond to the number of elements in the grid of income states and assets, respectively.

where $u_j(Y, A) = C_j(Y, A)^{-\gamma}$ and $\mathbb{E}_{Y'|Y}\left[u_j(Y', A'_j(Y, A))\right] = \int_{\underline{Y}}^{\overline{Y}}[u_j(Y', A'_j(Y, A))dF(Y'|Y)$, with $dF(Y'|Y)$ being the conditional probability density function of income.

2. Assume the borrowing constraint binds. Note that when the constraint binds we have that consumption is $C_{j+1}(Y, A) = Y + A(1+r) + \bar{A}$. We check whether this assumption holds by calculating the residual of the Euler equation:

$$\mathcal{R}(Y, A) = u_{j+1}(Y, A) - \beta(1 + r)\mathbb{E}_{Y'|Y}\left[u_j(Y', A'_j(Y, A))\right]. \tag{18}$$

If $\mathcal{R}(Y, A) > 0$, we keep the values for $C_{j+1}(Y, A)$. Otherwise, the constraint does not bind for that point of the state space and we discard $C_{j+1}(Y, A)$. We then solve for the value of $C_{j+1}(Y, A)$ that satisfies

$$C_{j+1}(Y, A)^{-\gamma} = \beta(1 + r)\mathbb{E}_{Y'|Y}\left[u_j(Y', A'_j(Y, A))\right]. \tag{19}$$

3. Use the resource constraint to obtain the updated conjecture for asset holdings $A'_{j+1}(Y, A) = Y + A(1 + r) - C_{j+1}(Y, A)$.

4. Check for convergence. If $||A'_{j+1}(Y, A) - A'_j(Y, A)|| < \epsilon$, then the problem is solved. Otherwise, discard A'_j and use A'_{j+1} as the new guess for the problem (go back to step 1).

C.2 Computation of Impulse Response Functions

In order to calculate the impulse response functions we follow a procedure similar to the one used in Gilchrist et al. (2014). For the response to aggregate shocks, we simulate an economy where the aggregate shock is set to its long-run average for 400 periods. Then we shock the economy at period 401 and compare it to a counterfactual economy where the aggregate shock remains at its long-run average. The difference in responses is what we report as the impulse response function. For the response to idiosyncratic shocks, we follow a similar process with the exception that at period 401 every agent in the economy receives a positive idiosyncratic shock of the same magnitude. We then aggregate responses using the joint distribution of income and assets. This approach calculates the average impulse response for individuals drawn from the steady-state distribution.

C.3 The Distribution of Consumption-Income Elasticities

In Section 3.2.3 we explored the consumption elasticity to aggregate income. It is also possible to calculate the generic consumption-income elasticity; we do so in this appendix and describe how it is distributed in the model economy.

We calculate $CIE_{i,t}$, the consumption-income elasticity (CIE) of household i in period t:

$$CIE_{i,t} = \frac{\log(C_{i,t}) - \log(C_{i,t-1})}{\log(Y_{i,t}) - \log(Y_{i,t-1})} \tag{20}$$

Throughout the paper, we study the CIE rather than the well-known MPC in order to directly compare with GOP's evidence. Figure 9 presents the ergodic distribution of CIEs under incomplete and full information. The incomplete information economy features smaller CIEs on average because agents in this economy are worse forecasters and thus have a stronger precautionary savings motive. Idiosyncratic shocks drive most income changes, and agents with full information can immediately observe that these shocks have persistent effects, so they change consumption more elastically than the incomplete information agents. Some CIEs are negative because agents may see their income increase, but by less than they expect, so they reduce consumption in response. This is less common under full information, where the AR(1) structure makes such events less likely. The full information distribution also has larger mass at one, because full information households are much more likely to be borrowing constrained, as shown in Figure 2.

Why is aggregate consumption so much more volatile when information is incomplete if the CIEs are lower than under full information? Crucially, the CIEs are different in response

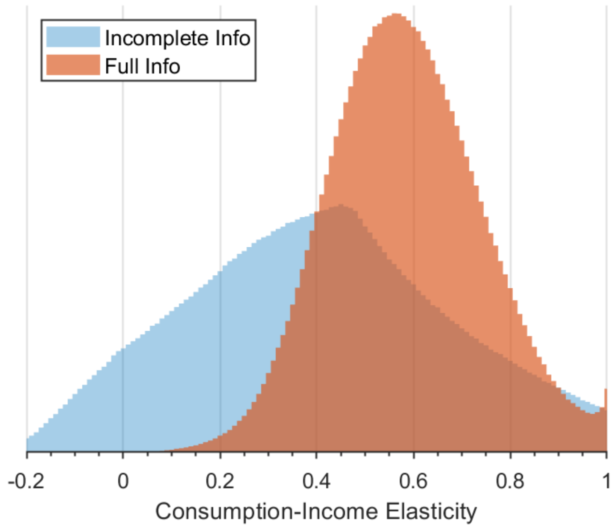


Figure 9: Ergodic Distributions of Consumption-Income Elasticities

Notes: The ergodic distributions of household-level CIEs are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. CIEs in the plotted distributions are only included for households experiencing income changes of one standard deviation or more in absolute value.

to idiosyncratic versus aggregate income changes. When we distinguish the generic CIE from the consumption elasticity to *aggregate* income shocks, we find that the incomplete information households are *more* elastic to aggregate income changes. This is the distinction that we explore in Section 3.2.3.

How can the general CIEs be so different from the CIEs to aggregate shocks (Figure 4) which were much lower under full information? The full information households are extremely elastic to idiosyncratic shocks which drive the majority of income changes, but less elastic to aggregate income changes which are much less persistent. However incomplete information households have similar elasticities to both types of shocks, because they cannot distinguish between them.

D Model Extensions

Section 3.3 described two extensions to the model that allow aggregate shocks to affect households heterogeneously. In this appendix we provide additional details about solving these models, and describing their equilibria. The first extension allows for heterogeneous skill types, where each skill type differs in terms of how sensitive their labor income is to aggregate income fluctuations. The second extension considers the possibility that agents may lose their jobs. We assume that, under incomplete information, households cannot perfectly observe the aggregate state of the economy while being unemployed (this is also the case when employed, as described in our main model).

D.1 Heterogeneity Across Skill Types

In this section, we are extending our baseline model by relaxing the assumption that all agents draw their income from the same stochastic process. In particular, we assume that there are K types of agents that have different elasticities to aggregate income. The purpose of this extension is to give our model more flexibility to accommodate heterogeneous skill types that differ in terms of how their income depends on aggregate income.

D.1.1 Model

The model builds on the baseline case. The main departure arises in the number of agent types that we consider. Agents of type k receive income determined by

$$\ln Y_{i,k,t} = \ln Y_{i,t}^{I} + \alpha_k^G \ln Y_t^G + \ln \kappa_k$$

where $Y_{i,t}^{I}$ and Y_t^G are determined as before. Note that in this setup, the income that type-k household receives has an elasticity α_k^G with respect to aggregate income. Thus, household types with larger α_k^G are more *sensitive* to aggregate income fluctuations than their peers with lower elasticities. κ_k denotes an average income shifter, which we use include so that our model is able to match relative income of different type of agents.

Within-type average incomes in period t are given by

$$\bar{Y}_{k,t} = \bar{Y}^I (Y_t^G)^{\alpha_k^G} \kappa_k$$

where $\bar{Y}^I \equiv \int_i (Y_{i,t}^I)^{\alpha_k^I} di$ is calculated by

$$\bar{Y}^I = e^{V_I/2}$$

because $(Y_{i,t}^I)$ is log-normal with $\ln Y_{i,t}^I \sim N(0, V_I)$ where $V_I \equiv \frac{\sigma_I^2}{1-\rho_I^2}$. Similarly, within-type unconditional average incomes are

$$\bar{Y}_k = \bar{Y}^I e^{(\alpha_k^G)^2 V_G/2} \kappa_k$$

where $V_G \equiv \frac{\sigma_G^2}{1-\rho_G^2}$. The rest of the model setup is identical to the baseline model.

D.1.2 Quantitative Analysis

Calibration and Solution Method For tractability, we assume 2 types of agents: unskilled and skilled. We use data on labor earnings reported in the CPS, and define "skilled" workers be anyone with some college or more and "unskilled" to be the remainder. Using state-level data from 1977-2022 we find that the average wage premium is 2.21, the average share of skilled workers is 0.49, the elasticity of skilled earnings to state income is 0.35, and the elasticity of unskilled earnings is 0.14.

We choose the elasticities α_U^G and α_S^G to match the *difference* in elasticities estimated in the data (which we define as $\Delta_{S,U} \equiv \alpha_S^G - \alpha_U^G$, while keeping the average elasticity unchanged from the baseline). Let s denote the share of skilled workers; this restriction gives the system of equations:

$$s\alpha_S^G + (1-s)\alpha_U^G = 1$$

$$\alpha_S^G - \alpha_U^G = 0.21$$

which implies $\alpha_S^G = 1.103$ and $\alpha_U^G = 0.897$. Then, we choose the remaining parameters κ_U and κ_S to again keep the average income level unchanged, while matching the average skill premium:

$$\frac{\bar{Y}_S}{\bar{Y}_U} = \frac{e^{(\alpha_S^G)^2 V_G/2} \kappa_S}{e^{(\alpha_U^G)^2 V_G/2} \kappa_U}$$

$$s\bar{Y}_S + (1-s)\bar{Y}_U = \bar{Y}^I e^{V_G/2}.$$

Replacing and solving for κ_U and κ_S, we have that $\kappa_U = 0.63$ and $\kappa_S = 1.39$. The last parameter that we calibrate is the discount factor. We set $\beta = 0.939$ so that the average wealth-to-income ratio in the incomplete information case is equal to 8, as in our baseline calibration. Table 8 presents a summary of the newly calibrated parameters in this extension.

Parameter	Interpretation	Value	Reference
β	Discount factor	0.939	U.S. net-worth-to-earnings ratio of 8
α_U^G	Sensitivity to aggregate income, unskilled	0.897	CPS
α_S^G	Sensitivity to aggregate income, skilled	1.103	CPS
$\bar{Y}_S/\bar{Y}_U$	Wage skill premium	2.21	CPS
κ_U	Relative income mean, unskilled	0.63	Internal
κ_S	Relative income mean, skilled	1.39	Internal

Table 8: Calibration - Heterogeneous Skill Types Model

The solution method is the same as the one used in the baseline, and is described in detail in Appendix C.1. We follow the same method for discretizing the income process that we used in the baseline scenario.[23] Once obtained the policy functions, we proceed to generate simulated time series from the model. For this, we assume that roughly half of the population is of the unskilled type, while remaining half is of the skilled type (consistent with the average share of skilled workers observed in the data).

Quantitative Results We start this section by providing a description of key long-run moments for the full and incomplete information models, which we present in Table 9. The results show that when we allow for heterogeneous skill types consumption and savings are

[23]The size of the state space under incomplete (full) information is $11 \times 11 \times 11 \times 250$ ($11 \times 11 \times 250$).

more volatile and less autocorrelated than in the baseline. This occurs for both information structures. What we also observe is that consumption is slightly lower than in the baseline, which is fueled by lower savings. This happens in the full and incomplete cases.

When contrasting information structures within the heterogeneous skill type model, we see that the same patterns of Table 2 arise here: aggregate consumption growth is substantially more volatile (44%) under incomplete information. In the cross-section we see that the information friction increases savings motives (larger savings) which reduces wealth inequality. This leads to observing higher levels of consumption under incomplete information.

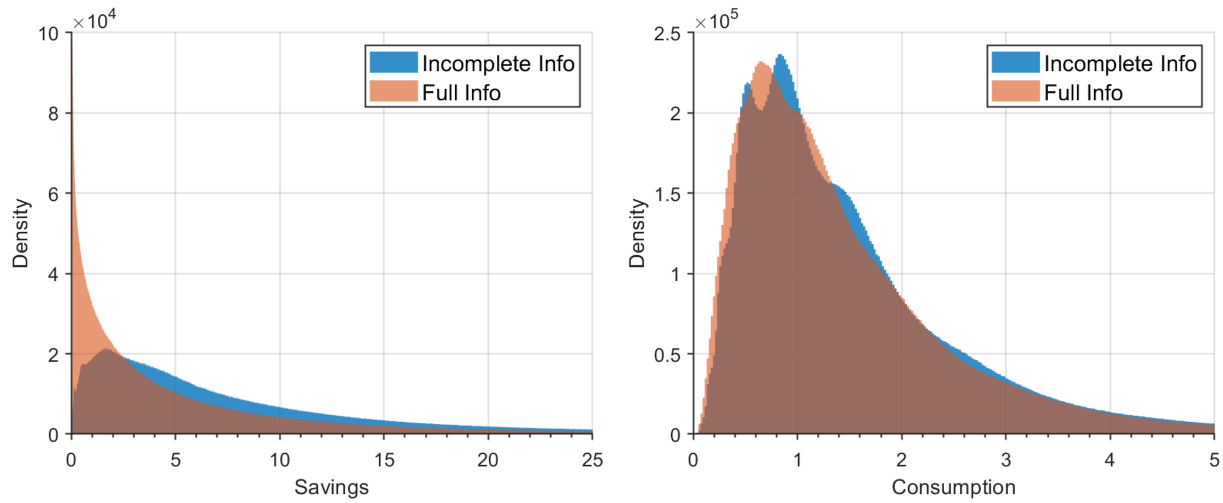
	Full Information	Incomplete Information
Aggregate Dynamics		
Consumption: Standard Deviation (log change)	0.009	0.013
Consumption: Autocorrelation	0.975	0.950
Assets: Standard Deviation (log change)	0.008	0.0042
Assets: Autocorrelation	0.997	0.997
Cross-Sectional Statistics		
Income: Mean	1.38	1.38
Income: Coefficient of Variation	1.08	1.08
Consumption: Mean	1.51	1.57
Consumption: Coefficient of Variation	0.82	0.80
Consumption: Autocorrelation	0.99	0.99
Assets: Mean	6.28	9.53
Assets: Coefficient of Variation	1.58	1.24
Assets: Autocorrelation	1.00	1.00

Notes: Long-run moments are calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models.

Table 9: Long-run Moments - Heterogeneous Skill Types Model

Figure 10 presents the ergodic distribution for assets and consumption. Similarly to what we observed previously, the information friction pushes households to save more due to their inability to distinguish between aggregate and idiosyncratic shocks. This effect is especially strong at the left tail of the distribution, where the credit- constrained or low savings households are present. The larger asset holdings under incomplete information allow households to experience larger levels of consumption due to the additional return on their savings, which explains the shifted consumption distribution in panel (b).

Until this point, we see that allowing for heterogeneous skill types does not alter significantly the conclusions that we draw from the long-run moments of the model. In what remains of this section we analyze whether the rest of the key findings of the baseline model hold in this model extension. Specifically, we study the impulse response functions to aggregate and idiosyncratic shocks to assess whether the "flipped" observed in the baseline model are still present. Additionally, we also study if the result of elevation and homogenization of the consumption-income elasticities to aggregate shock still prevails in this extension.



(a) Assets (b) Consumption

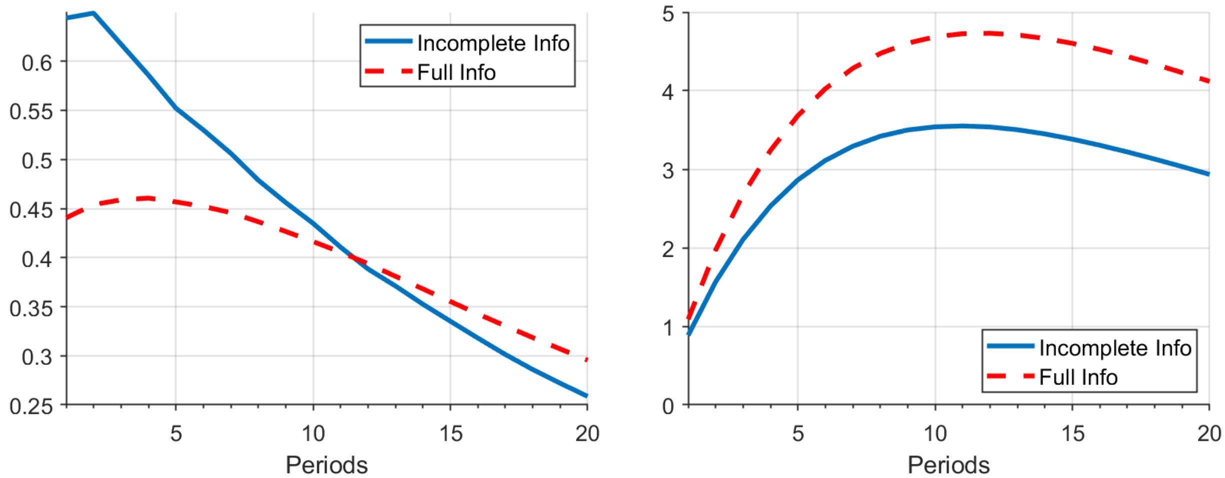
Figure 10: Ergodic Distributions - Heterogeneous Skill Types Model

Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. Both distributions extend outside the axis range, but the right tails are omitted for readability.

Figure 11 presents the impulse response functions of consumption and asset holdings to aggregate shocks, while Figure 12 does the same but for idiosyncratic shocks.[24] Interestingly, the responses to aggregate and idiosyncratic income shocks are very similar to those of the case with homogeneous skill types. The main difference is a small one and is related to the magnitude of consumption responses. In particular, we observe that under full and incomplete information consumption responses tend to be slightly stronger to income shocks

[24] We construct impulse response functions for each type, within each information structure. The approach we follow to do so is identical to the one described in Appendix C.2.

when we have heterogeneous skill types. Note that stronger consumption responses imply weaker savings responses.

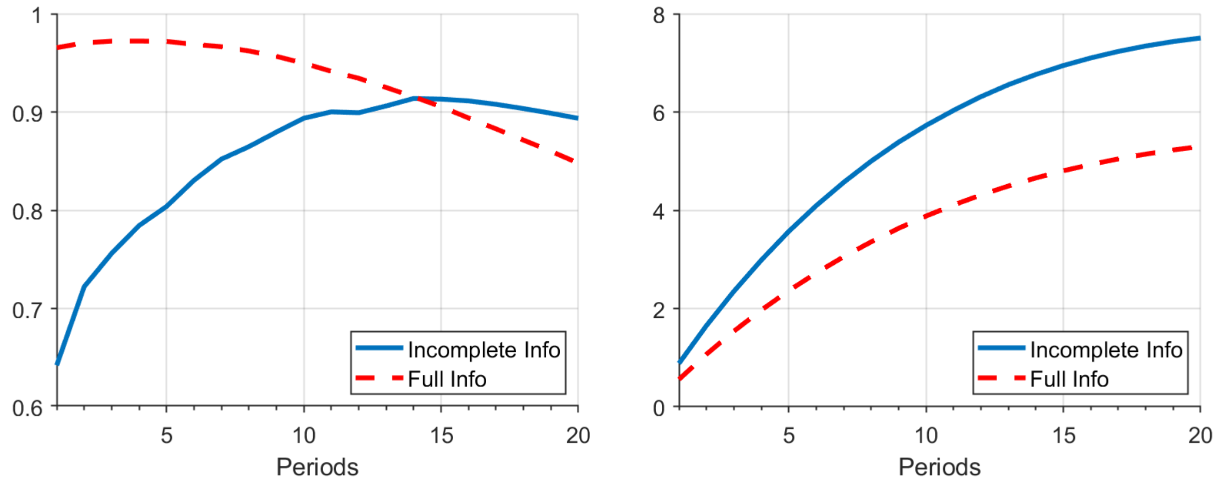


(a) Consumption

(b) Assets

Figure 11: Impulse Responses to an Aggregate Income Shock - Heterogeneous Skill Types Model

Notes: Impulse response functions are calculated by subjecting the economy to a one standard deviation aggregate income shock, and comparing with a counterfactual economy receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.



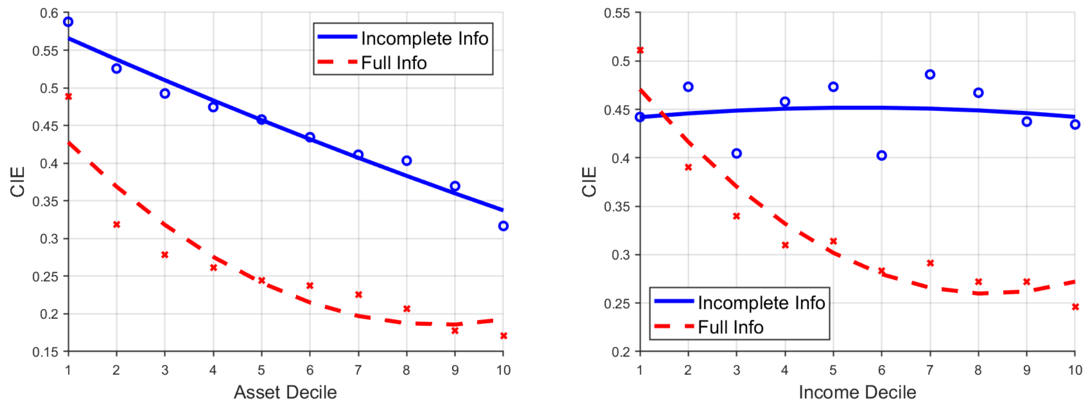
(a) Consumption

(b) Assets

Figure 12: Impulse Responses to an Idiosyncratic Income Shock - Heterogeneous Skill Types Model

Notes: Impulse response functions are calculated by subjecting a household to a one standard deviation idiosyncratic income shock, and comparing it with a counterfactual household receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.

The last result we want to highlight is that the consumption-income elasticity to aggregate income shocks continues to exhibit the properties of elevation and homogeneization across income deciles. Figure 13 presents the aforementioned elasticities across wealth and income deciles.



(a) Elasticities by Wealth

(b) Elasticities by Income

Figure 13: Consumption-Income Elasticities to Aggregate Income - Heterogenous Skill Types Model

Notes: The solid and dashed curves are fit from quadratic regressions. The distributions of CIE^G are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and shocks for both models. The elasticity is calculated at the household level and averaged within household groups corresponding to the asset or income deciles of the incomplete information model's ergodic distribution. Households are grouped based on their position in period $t-1$ for a shock that occurs in period t. The plotted elasticities only include periods with aggregate shocks exceeding two standard deviations in absolute value.

The average consumption-income elasticity to aggregate income shocks is 0.45 under incomplete information, larger than its full information counterpart which is 0.33. The elevation of the CIE^G under incomplete information is still present. In fact, both elasticities are larger than in the baseline scenario, suggest that having heterogeneous skill types tends to further increase the response of consumption to aggregate income shocks. Another feature we observe is that the homogenization of the CIE^G across income deciles is also present under incomplete information. The CIE^G is quite stable across the income distribution.

In conclusion, we show that an extension that features households with different skill types, this is, where they are asymmetrically affected by aggregate income fluctuations, is able to replicate key findings in the baseline model. It is important to note that the quantitative results of the heterogeneous skill types framework may crucially depend how the income of unskilled and skilled households is affected by aggregate income. We acknowledge this potential concern, so we provide a robustness analysis in Appendix F.3.3 where we vary the gap of elasticities to aggregate income across skill types. The main findings of this robustness analysis show that the main quantitative results of this extension are not substantially different if we were to consider alternative values for this elasticity gap.

D.2 Unemployment Risk

Our baseline setup assumes that at every point in time, households are employed and receive labor income. This assumption can be restrictive under incomplete information because changes to the extensive margin of employment could potentially give information to households about the aggregate state of the economy. To address this concern we provide an extension of our baseline model, where we allow agents to move from employed to unemployed and vice versa.

D.2.1 Model

In every period, we assume that agents stochastically move into or out of an unemployment state. While unemployed, we assume that agents receive an unemployment benefit which is a fraction b of the income $Y_{i,t}$ they would have received if they had been employed. This is a standard assumption (Krueger et al., 2016) but is especially valuable in our setting for tractability purposes; the household's forecasting problem is simplified because they always receive the information that they would have received if employed.

The employment transition probabilities depend on aggregate log income. These probabilities are given by

$$s_t = \psi_s \ln Y_t^G + \overline{s} \tag{21}$$

$$f_t = \psi_f \ln Y_t^G + \overline{f} \tag{22}$$

where s_t and f_t denote the separation and job-finding rate in period t, respectively.

Information Structure We assume agents observe noisy signals of the transition probabilities. Every time an agent finds or loses a job, they get information about the aggregate state of the economy. And if they learn that other agents find or lose jobs, they learn even more. This kind of small sample observation is a noisy signal of the true transition probabilities with asymptotically normal error. For tractability, we simply model agents as receiving signals with normal noise:[25]

$$z^s_{i,t} = s_t - \overline{s} + \varepsilon^s_{i,t} \tag{23}$$

$$z^f_{i,t} = f_t - \overline{f} + \varepsilon^f_{i,t} \tag{24}$$

with independent noise shocks $\varepsilon^s_{i,t} \sim N(0, \sigma^2_{\varepsilon^s})$ and $\varepsilon^f_{i,t} \sim N(0, \sigma^2_{\varepsilon^f})$. The presence of noisy signals implies that we need to redefine the information structure that agents face under incomplete information.

The noise shocks are independent of other shocks in the model, so this structure reduces to a single combined noisy signal of $\ln Y^G_t$:

$$\mathbb{E}[\ln Y^G_t | z^s_{i,t}, z^f_{i,t}] = \mathbb{E}\left[\ln Y^G_t \middle| \frac{z^s_{i,t}}{\psi_s}, \frac{z^f_{i,t}}{\psi_f}\right]$$

$\frac{z^s_{i,t}}{\psi_s}$ and $\frac{z^f_{i,t}}{\psi_f}$ are noisy signals of $\ln Y^G_t$ with noise variances $\frac{\sigma^2_{\varepsilon^s}}{\psi^2_s}$ and $\frac{\sigma^2_{\varepsilon^f}}{\psi^2_f}$. Therefore the expectation is given by

$$= \frac{\mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^f}}{\psi^2_f}}{\mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^f}}{\psi^2_f} + \mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^s}}{\psi^2_s} + \frac{\sigma^2_{\varepsilon^s}}{\psi^2_s} \frac{\sigma^2_{\varepsilon^f}}{\psi^2_f}} \frac{z^s_{i,t}}{\psi_s} + \frac{\mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^s}}{\psi^2_s}}{\mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^f}}{\psi^2_f} + \mathrm{Var}\left(y^G_t\right) \frac{\sigma^2_{\varepsilon^s}}{\psi^2_s} + \frac{\sigma^2_{\varepsilon^s}}{\psi^2_s} \frac{\sigma^2_{\varepsilon^f}}{\psi^2_f}} \frac{z^f_{i,t}}{\psi_f},$$

which we write in terms of aggregate and idiosyncratic components by:

$$= \psi_c \ln Y^G_t + \psi_c \varepsilon^c_{i,t},$$

[25]This is a standard shortcut in these types of settings where the modeler would like agents to learn some information but not the true state of the world (Lorenzoni, 2009).

where

$$\psi_c \equiv \frac{\mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2} + \mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^s}}{\psi_s^2}}{\mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2} + \mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^s}}{\psi_s^2} + \frac{\sigma^2_{\varepsilon^s}}{\psi_s^2}\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2}}$$

with error

$$\psi_c \varepsilon^c_{i,t} = \frac{\mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2}\frac{\varepsilon^s_{i,t}}{\psi_s} + \mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^s}}{\psi_s^2}\frac{\varepsilon^f_{i,t}}{\psi_f}}{\mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2} + \mathrm{Var}\left(y_t^G\right)\frac{\sigma^2_{\varepsilon^s}}{\psi_s^2} + \frac{\sigma^2_{\varepsilon^s}}{\psi_s^2}\frac{\sigma^2_{\varepsilon^f}}{\psi_f^2}}$$

Then lastly define the single combined noisy signal $\zeta_{i,t}$ as

$$\zeta_{i,t} = \ln Y_t^G + \varepsilon^c_{i,t}$$

with $\varepsilon^c_{i,t} \sim N(0, \sigma^2_{\varepsilon^c})$, where

$$\sigma^2_{\varepsilon^c} \equiv \frac{\sigma^2_{\varepsilon^f}\sigma^2_{\varepsilon^s}}{\sigma^2_{\varepsilon^f}\psi_s^2 + \sigma^2_{\varepsilon^s}\psi_f^2}$$

With this structure, the noisy signal $\zeta_{i,t}$ follows an ARMA(1,1) process. With lag operator notation, the Wold representation is:

$$\zeta = y^G + \varepsilon^c$$

$$= \frac{1 + \vartheta L}{1 - \rho_G L} v$$

where v is the white noise forecast error process, satisfying

$$v = \frac{1}{1 + \vartheta L} u^G + \frac{1 - \rho_G L}{1 + \vartheta L} \varepsilon^c$$

with the scalar ϑ to be found. The time series $v_{i,t}$ is given by

$$v_{i,t} = v^u_{i,t} + v^\varepsilon_{i,t} - \rho_G v^\varepsilon_{i,t-1} \tag{25}$$

where

$$v^u_t = -\vartheta v^u_{t-1} + u^G_t \qquad v^\varepsilon_{i,t} = -\vartheta v^\varepsilon_{i,t-1} + \varepsilon^c_{i,t}$$

ϑ and $\text{Var}(v)$ must satisfy two equations. First, $\text{Var}((1+\vartheta L)v) = \text{Var}(u^G + (1-\rho_G L)\varepsilon^c)$ implies

$$(1+\vartheta^2)\text{Var}(v) = \sigma_G^2 + (1+\rho_G^2)\sigma_{\varepsilon^c}^2$$

Second, $\text{Cov}((1+\vartheta L)v, L(1+\vartheta L)v) = \text{Cov}(u^G + (1-\rho_G L)\varepsilon^c, Lu^G + L(1-\rho_G L)\varepsilon^c)$ implies

$$\vartheta\text{Var}(v) = -\rho_G\sigma_{\varepsilon^c}^2$$

Thus ϑ is the stable solution to the quadratic equation

$$\vartheta^2 + \frac{\sigma_G^2 + (1+\rho_G^2)\sigma_{\varepsilon^c}^2}{\rho_G\sigma_{\varepsilon^c}^2}\vartheta + 1 = 0$$

Information Set Evolution The exogenous component of the household's information set now evolves by

$$\Omega_{i,t} = \{\Omega_{i,t-1}, Y_{i,t}, \zeta_{i,t}\} \tag{26}$$

but there is a simpler recursive representation. Write log income $y_{i,t}$ in terms of the forecast error $\omega_{i,t}$ and the prior forecast:

$$y_{i,t} = \omega_{i,t} + \mathbb{E}_{i,t-1}[y_{i,t}]$$

$y_{i,t}$ is still an ARMA(2,1) given by equation (14), but with the additional information from the noisy signal, the original forecast errors $w_{i,t}$ are now partially forecastable. The expectation of next period's income becomes:

$$\mathbb{E}_{i,t}[y_{i,t+1}] = \varrho_0 y_{i,t} + \varrho_1 y_{i,t-1} + \theta w_{i,t} + \mathbb{E}_{i,t}[w_{i,t+1}]$$

The expectation of $w_{i,t+1}$ is

$$\mathbb{E}_{i,t}[w_{i,t+1}] = \mathbb{E}[w_{i,t+1}|\{\zeta_{i,t-j}\}_{j=0}^{\infty}]$$

but the idiosyncratic component of $w_{i,t+1}$ is orthogonal to all lags of $\zeta_{i,t}$, so by equation (13):

$$= \mathbb{E}\left[\frac{1-\rho_I L}{1+\theta L} u^G_{t+1} | \{\zeta_{i,t-j}\}^{\infty}_{j=0}\right] = \mathbb{E}\left[\frac{-\theta-\rho_I}{1+\theta L} u^G_{t} | \{\zeta_{i,t-j}\}^{\infty}_{j=0}\right]$$

To construct the expectation of this sum of u^G_t's, first consider the backcast of any lag of u^G_t:

$$\mathbb{E}\left[L^k u^G_t | \{\zeta_{i,t-j}\}^{\infty}_{j=0}\right] = \mathbb{E}\left[L^k u^G_t | \{v_{i,t-j}\}^{\infty}_{j=0}\right] = \sum_{j=0}^{k} \frac{\mathrm{Cov}(u^G_{t-j}, v_{i,t-j})}{\mathrm{Var}(v_{i,t-j})} v_{i,t-j}$$

$$= \sum_{j=0}^{k} \frac{(-\vartheta)^{k-j}\sigma^2_G}{\mathrm{Var}(v)} v_{i,t-j}$$

Using these backcasts, the forecast of $w_{i,t+1}$ becomes

$$\mathbb{E}\left[\frac{-\theta-\rho_I}{1+\theta L} u^G_t | \{\zeta_{i,t-j}\}^{\infty}_{j=0}\right] = v_{i,t}\frac{(-\theta-\rho_I)\sigma^2_G}{\mathrm{Var}(v)}(1+\theta\vartheta+\theta^2\vartheta^2+...)$$

$$+v_{i,t-1}\frac{(-\theta-\rho_I)\sigma^2_G}{\mathrm{Var}(v)}(-\theta-\theta^2\vartheta-\theta^3\vartheta^2+...) + v_{i,t-2}\frac{(-\theta-\rho_I)\sigma^2_G}{\mathrm{Var}(v)}(\theta^2+\theta^3\vartheta+\theta^4\vartheta^2+...)$$

$$= \frac{(-\theta-\rho_I)\sigma^2_G}{(1+\theta^2\vartheta^2)\mathrm{Var}(v)} \frac{1}{1+\theta L} v_{i,t}$$

This forecast is AR(1) with autocorrelation $-\theta$; denote the forecast by $f^w_{i,t} \equiv \mathbb{E}_{i,t}[w_{i,t+1}]$. Thus $f^w_{i,t}$ is given recursively by

$$f^w_{i,t} = -\theta f^w_{i,t-1} + \frac{(-\theta-\rho_I)\sigma^2_G}{(1+\theta^2\vartheta^2)\mathrm{Var}(v)} v_{i,t} \tag{27}$$

which gives $\omega_{i,t}$ by

$$\omega_{i,t} = w_{i,t} - f^w_{i,t-1} \tag{28}$$

Then the VAR(1) representation for the income process becomes

$$\boldsymbol{y}_{i,t} \equiv \begin{pmatrix} y_{i,t} \\ y_{i,t-1} \\ w_{i,t} \\ f^w_{i,t} \end{pmatrix}$$

with coefficient matrix $B = \begin{pmatrix} \varrho_0 & \varrho_1 & \theta & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & -\theta \end{pmatrix}$ and innovation $C \begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix}$. $\omega_{i,t}$ appears because the forecast error for $y_{i,t}$ is also the forecast error for $w_{i,t}$. With coefficient matrix $C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & c_{f,v} \end{pmatrix}$ where $c_{f,v} \equiv \frac{(-\theta-\rho_I)\sigma_G^2}{(1+\theta^2\vartheta^2)\mathrm{Var}(v)}$, the VAR(1) system is

$$\boldsymbol{y}_t = B\boldsymbol{y}_{i,t-1} + C \begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix}$$

Finally, we need to determine the variance of $\omega_{i,t}$:

$$\mathrm{Var}(\omega) = \mathrm{Var}(w) - \mathrm{Var}(f^w)$$

$$\mathrm{Var}(f^w) = \left(\frac{(-\theta-\rho_I)\sigma_G^2}{(1+\theta^2\vartheta^2)\mathrm{Var}(v)} \right)^2 \frac{\mathrm{Var}(v)}{1-\theta^2}$$

Thus the variance of $C \begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix}$ is

$$Var\left(C \begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix} \right) = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & c_{f,v} \end{pmatrix} \begin{pmatrix} Var(\omega) & 0 \\ 0 & Var(v) \end{pmatrix} \begin{pmatrix} 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & c_{f,v} \end{pmatrix}$$

$$= \begin{pmatrix} Var(\omega) & 0 & Var(\omega) & 0 \\ 0 & 0 & 0 & 0 \\ Var(\omega) & 0 & Var(\omega) & 0 \\ 0 & 0 & 0 & c_{f,v}^2 Var(v) \end{pmatrix}$$

Income and State Transitions Unemployment introduces an additional state variable. In the baseline model, the household's state is $\Omega_{i,t}$, the vector that encodes their income and information. Now, we introduce an additional state $U_{i,t}$: their unemployment status, taking value 1 if unemployed and 0 otherwise.

The agent's perceived transition between unemployment states is:

$$\Pr(U_{i,t+1} = 0 | U_{i,t} = 1) = \mathbb{E}_{i,t}[f_{t+1}] = \overline{f} + \psi_f \mathbb{E}_{i,t}[Y_{t+1}^G]$$

$$\Pr(U_{i,t+1} = 1 | U_{i,t} = 1) = 1 - \mathbb{E}_{i,t}[f_{t+1}] = 1 - \overline{f} - \psi_f \mathbb{E}_{i,t}[Y_{t+1}^G]$$

$$\Pr(U_{i,t+1} = 0 | U_{i,t} = 0) = 1 - \mathbb{E}_{i,t}[s_{t+1}] = 1 - \overline{s} - \psi_s \mathbb{E}_{i,t}[Y_{t+1}^G]$$

$$\Pr(U_{i,t+1} = 1 | U_{i,t} = 0) = \mathbb{E}_{i,t}[s_{t+1}] = \overline{s} + \psi_s \mathbb{E}_{i,t}[Y_{t+1}^G]$$

Accordingly, it becomes relevant to track agents' forecasts of aggregate income $\mathbb{E}_{i,t}[Y_{t+1}^G]$.

It is useful to express this forecast in terms of the nowcast:

$$\mathbb{E}_{i,t}[Y^G_{t+1}] = \rho_G \mathbb{E}_{i,t}[Y^G_t]$$

and track the evolution of the nowcast recursively. The nowcast follows

$$\mathbb{E}_{i,t}[Y^G_t] = \rho_G \mathbb{E}_{i,t-1}[Y^G_{t-1}] + \alpha_\omega \omega_{i,t} + \alpha_v v_{i,t}$$

where the coefficients α_ω and α_v depend nonlinearly on the parameters of the income process and σ_{ε^c}.

The forecast of aggregate income $f^G_{i,t} \equiv \mathbb{E}_{i,t}[y^G_{t+1}]$ now becomes a state variable since it affects consumption and savings decisions of households. The updated VAR(1) formulation for the exogenous state variables under incomplete information is then

$$\boldsymbol{y}_{i,t} \equiv \begin{pmatrix} y_{i,t} \\ y_{i,t-1} \\ w_{i,t} \\ f^w_{i,t} \\ f^G_{i,t} \end{pmatrix}$$

with coefficient matrix $B = \begin{pmatrix} \varrho_0 & \varrho_1 & \theta & 1 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -\theta & 0 \\ 0 & 0 & 0 & 0 & \rho_G \end{pmatrix}$ and innovation $C \begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix}$. The coefficient matrix is now

$$C = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & c_{f,v} \\ \rho_G\alpha_\omega & \rho_G\alpha_v \end{pmatrix}$$

so that the VAR(1) system is

$$\boldsymbol{y}_t = B\boldsymbol{y}_{i,t-1} + C\begin{pmatrix} \omega_{i,t} \\ v_{i,t} \end{pmatrix}$$

Recursive Formulation With the information structure completely characterized we can now provide a description of the recursive problem faced by households in the economy. Under full information, the problem that the household faces is

$$\begin{aligned} V^e(y^I, y^G, A) = \max_{A'} \Bigg\{ & \frac{\left(\tilde{Y}(1-\tau) + (1+r)A - A'\right)^{1-\gamma}}{1-\gamma} \\ & + \beta\mathbb{E}\left[(1-s(y^{G'}))V^e(y^{I'}, yG', A') + s(y^{G'})V^u(y^{I'}, y^{G'}, A')\right]\Bigg\} \end{aligned} \tag{29}$$

$$\begin{aligned} V^u(y^I, y^G, A) = \max_{A'} \Bigg\{ & \frac{\left(b\tilde{Y} + (1+r)A - A'\right)^{1-\gamma}}{1-\gamma} \\ & + \beta\mathbb{E}\left[f(y^{G'})V^e(y^{I'}, y^{G'}, A') + (1-f(y^{G'}))V^u(y^{I'}, y^{G'}, A')\right]\Bigg\}, \end{aligned} \tag{30}$$

where $\tilde{Y} = \exp(y^I + y^G)$ and τ is a labor income tax used to finance unemployment benefits.[26] V^e and V^u denote the value functions associated with being employed and unemployed, respectively. The transition probabilities between states are a function of the separation

[26] We assume that the government sets a constant tax such that, on average, its budget constraint is satisfied with equality. Whenever this is not the case, we assume that the government borrows/saves from abroad (since we assume the economy is small and open) to finance any deficits, or to save any surpluses. We numerically corroborate that the present value of the government surplus converges to 0, and that the average average surplus is close to 0 as well.

(s) and job-finding rates (f), which happen to be a function of the aggregate state of the economy.

The recursive formulation of the household's problem under incomplete information is the following:

$$V^e(\mathcal{X}, A) = \max_{A'} \Bigg\{ \frac{\left(\tilde{Y}(1-\tau) + (1+r)A - A'\right)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}\left[(1-s(f^G))V^e(\mathcal{X}', A') + s(f^G)V^u(\mathcal{X}', A')\right] \Bigg\} \tag{31}$$

$$V^u(\mathcal{X}, A) = \max_{A'} \Bigg\{ \frac{\left(b\tilde{Y} + (1+r)A - A'\right)^{1-\gamma}}{1-\gamma} + \beta \mathbb{E}\left[f(f^G)V^e(\mathcal{X}', A') + (1-f(f^G))V^u(\mathcal{X}', A')\right] \Bigg\}. \tag{32}$$

where $\mathcal{X} = (y, y_{-1}, w, f^w, f^G)$, and V^e (V^u) denotes the value function associated with being employed (unemployed).

D.2.2 Quantitative Analysis

Calibration and Solution Method Most of the parameters remain unchanged with respect to the baseline scenario.[27] Since many target moments do not vary importantly, we provide an explicit description of the calibration of those that either changed or were not present before.

We start by estimating the transition probabilities from the data. Let s_t denote the separation rate (the probability of leaving a job, conditional on employment), and f_t the job finding rate (the probability of finding a job, conditional on unemployment). Using state-level data from JOLTS, employment data from the BLS, and earnings data from the BEA,

[27] The discount factor that we set in the base calibration yields an asset-to-income ratio of roughly 8, which is the target observed in the data.

we estimate the following equations

$$s_t = \psi_s \ln Y_t^G + \overline{s}$$

$$f_t = \psi_f \ln Y_t^G + \overline{f}$$

We find that $\psi_s = -0.00872$ and $\psi_f = 0.0399$. To map the monthly JOLTS transition rates to annualized probabilities in the model, we construct the monthly Markov transition matrix, the 12th power of which gives the annual transition probabilities. The average annual values are $\overline{s} = 0.048$ and $\overline{f} = 0.952$.

Based on this process for the transition probabilities, we calibrate the noise variance $\sigma^2_{\varepsilon^c}$ to yield realistic household expectations behavior. Unfortunately, the SCE does not ask individuals to forecast unemployment; instead, it asks for their perceived probabilities that unemployment will increase over the following 12 months. We apply a probit regression to clean the responses and provide a rational forecast of the actual probability at the state level. Then, we use simulated method of moments to identify the value of σ_{ε^c} that reproduces the empirical average error in reported probabilities relative to the rational expectation. We estimate $\sigma_{\varepsilon^c} = 0.15$, which implies $\alpha_\omega = 0.01$ and $\alpha_v = 0.05$.

We set the labor income tax so that the average tax revenue equates the average unemployment benefit payout in the economy. For the unemployment benefit parameter b, we follow Krueger et al. (2016) and set $b = 0.5$. We then use the ergodic distribution to obtain average tax revenues and unemployment payouts. We set $\tau = 0.0255$ in the complete and incomplete information models, which is the value such that the government's lifetime budget constraint is satisfied. Table 10 presents a summary of the calibration of the new parameters in the unemployment risk extension.

Parameter	Interpretation	Value	Reference
ψ_s	Separation rate elasticity	-0.0087	JOLTS, BLS and BEA
$\bar{s}$	Average separation rate	0.048	JOLTS, BLS and BEA
ψ_f	Job-finding rate elasticity	0.040	JOLTS, BLS and BEA
$\bar{f}$	Average job-finding rate	0.952	JOLTS, BLS and BEA
σ_{ε^c}	Noise variance	0.150	SCE
b	Unemployment replacement ratio	0.5	Krueger et al. (2016)
α_ω	Y_t^G nowcast coefficient on $\omega_{i,t}$	0.010	Internal
α_v on $v_{i,t}$	Y_t^G nowcast coefficient	0.050	Internal
τ	Labor income tax	0.0255	Internal

Table 10: Calibration - Unemployment Risk Model

In order to numerically solve the model, we discretize the exogenous states following Tauchen (1986). For the full information case we keep the same discretized outcomes, while for the incomplete information we use a discretized version of the VAR(1) system presented above. The asset grid is the same as in the baseline.[28]

The solution method that we employ is a variation of the one described in Appendix C.1. The critical difference is that now we make guesses for policy functions A'_u and A'_e, and we use the Euler equations for the employed and unemployed states to update them.

Quantitative Results Table 11 presents the long-run moments for the model with unemployment risk, under full and incomplete information. Similarly to the findings described in Section 3.2.1, we observe that aggregate consumption is substantially more volatile under incomplete information (roughly 30% more), while the opposite occurs for savings (where savings are on average 31% less volatile under incomplete information). These two patterns are consistent with what we describe in the baseline model: the inability to distinguish between aggregate and idiosyncratic shock leads to worse forecasting, poorer consumption smoothing, and a stronger precautionary motive. This is corroborated by the large gap observed in average assets, where households under incomplete information save on average 22% more than if they could distinguish between aggregate and idiosyncratic shocks.

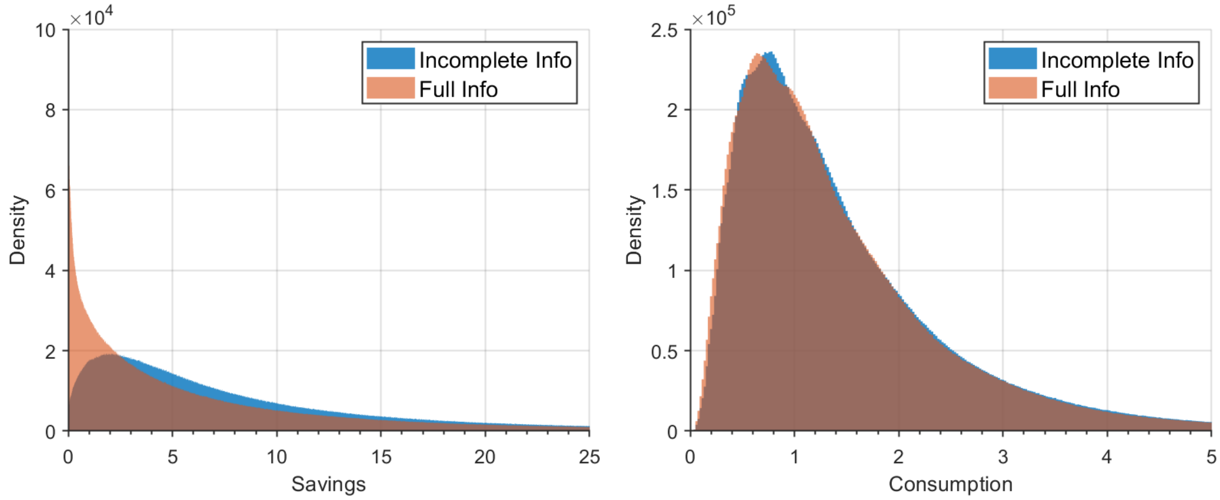
[28]For the full information case we consider grids of 11 points for each income level. The size of the state space is $11 \times 11 \times 250 \times 2$. For the incomplete information scenario, we consider 13 points for y and its lag, and 3 points for w, f^w, and f^G, respectively. The size of the state space is $13 \times 13 \times 3 \times 3 \times 3 \times 250 \times 2$.

	Full Information	Incomplete Information
Aggregate Dynamics		
Consumption: Standard Deviation (log change)	0.0079	0.0103
Consumption: Autocorrelation	0.980	0.968
Assets: Standard Deviation (log change)	0.0068	0.0047
Assets: Autocorrelation	0.997	0.997
Cross-Sectional Statistics		
Income: Mean	1.38	1.38
Income: Coefficient of Variation	0.94	0.94
Consumption: Mean	1.47	1.51
Consumption: Coefficient of Variation	0.80	0.80
Consumption: Autocorrelation	0.99	0.99
Assets: Mean	8.14	9.93
Assets: Coefficient of Variation	1.44	1.21
Assets: Autocorrelation	1.00	1.00

Notes: Long-run moments are calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models.

Table 11: Long-run Moments - Unemployment Risk Model

In the presence of unemployment risk, the cross-sectional behavior of assets and consumption does not differ substantially with the one observed in the baseline model. Figure 14 presents the ergodic distribution of aggregate assets and consumption for the two models when there is unemployment risk. Panel (a) shows that, as in our baseline scenario, the information friction especially distortions asset levels close to the borrowing limit, which is the area that agents wish to avoid when receiving a shock of an unknown nature (aggregate or idiosyncratic). Thus, precautionary motives are still strong in comparison to the full information case and hence push agents to save more aggressively.



(a) Assets (b) Consumption

Figure 14: Ergodic Distributions - Unemployment Risk Model

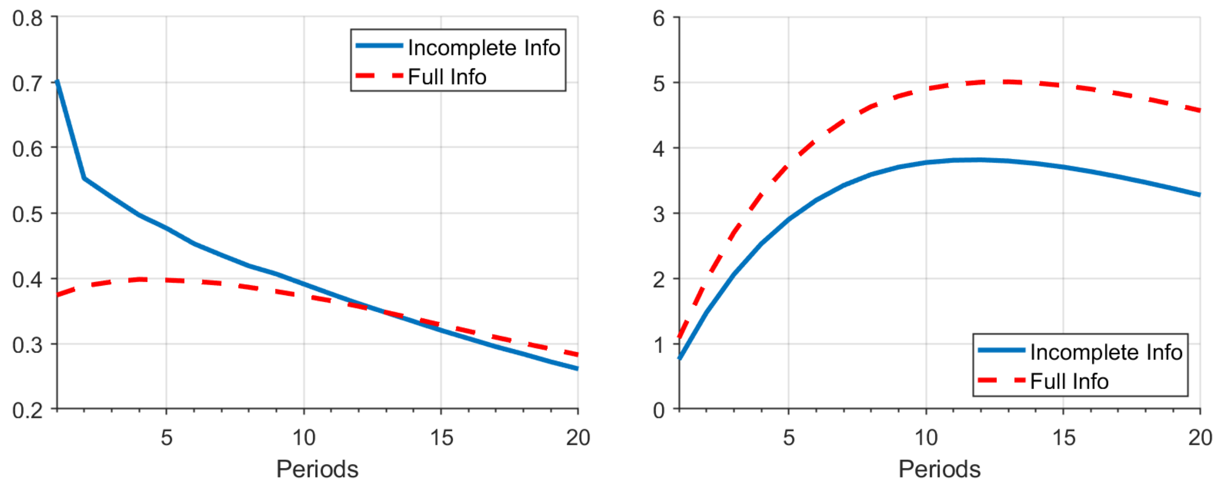
Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate, idiosyncratic and unemployment shocks for both models. Both distributions extend outside the axis range, but the right tails are omitted for readability.

Do we observe similar patterns in terms of asset and consumption responses to aggregate and idiosyncratic shocks? In order to answer this question, we replicate the analysis of Section 3.2.2. In particular, we generate the equivalent impulse response functions to those shown previously in Figure 3.[29] Figures 15 and 16 present the impulse response functions of aggregate consumption and assets to aggregate and idiosyncratic income shocks, respectively. As in our baseline scenario, the magnitude of the shocks is one standard deviation forecast error for log income.

The results presented in Figure 15 show that the consumption and asset responses to an aggregate income shock differ importantly across information structures. In fact, the same patterns observed in Section 3.2.2 arise: the response of aggregate consumption is much larger under incomplete information, while the converse occurs for assets. Note that the aggregate

[29] We follow the same procedure for generating them. Note that since aggregate shocks affect the separation and job-finding rates, the on-impact effect will differ depending on whether the shock is aggregate or idiosyncratic for the incomplete information case. Recall that this was not the case in our baseline specification since the on-impact effects were identical for aggregate and idiosyncratic shocks under incomplete information.

consumption responses tend to converge at a slightly shorter time horizon, because agents can use their noisy observations of the labor market to learn about the aggregate state of the economy. Nevertheless, responses are quite dissimilar, especially on impact, due to the inability of agents to properly observe the nature of the income shock they are experiencing, and the additional income volatility agents face due to unemployment risk.



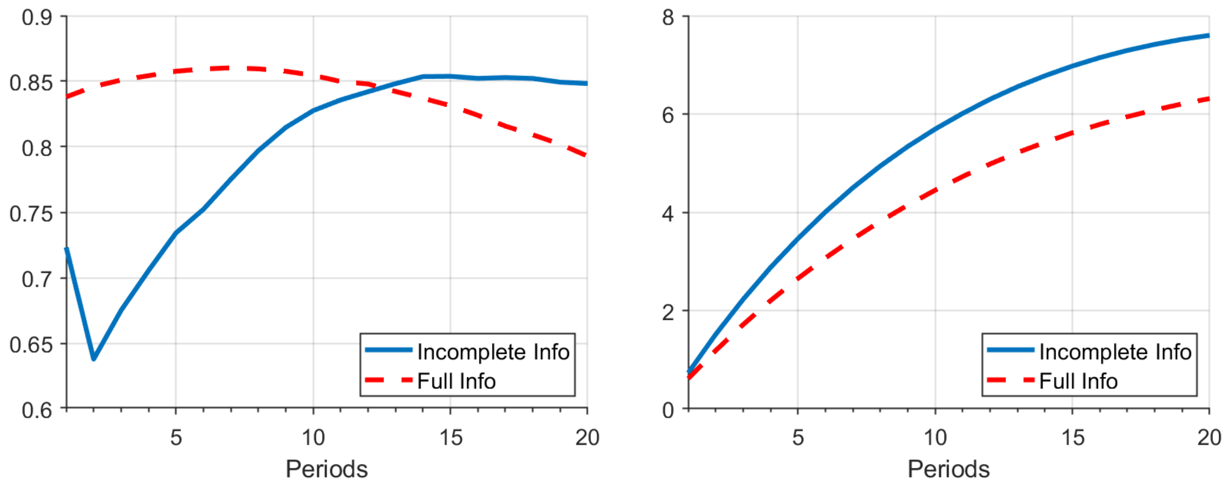
(a) Consumption

(b) Assets

Figure 15: Impulse Responses to an Aggregate Income Shock - Unemployment Risk Model

Notes: Impulse response functions are calculated by subjecting the economy to a one standard deviation aggregate income shock, and comparing with a counterfactual economy receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.

Figure 16 illustrates the responses of aggregate consumption and assets to an idiosyncratic shock. Qualitatively speaking, we see the same ordering (with respect to the baseline case) in terms of consumption and asset responses: consumption tends to *under-react* to an idiosyncratic shock, while savings *over-react*. Interestingly, we have that the full and incomplete information responses of consumption to the shock are milder relative to the scenario without unemployment risk. Intuitively, this occurs due to the presence of additional income risk: because agents can become unemployed they decide to save a larger fraction of their income, regardless of the nature of the shock they are experiencing. Additionally, we also see that the convergence in the consumption responses for the two information structures occurs earlier than for the baseline scenario. Again, this is because the unemployment model gives agents an additional signal from which they can learn about the aggregate economy.



(a) Consumption

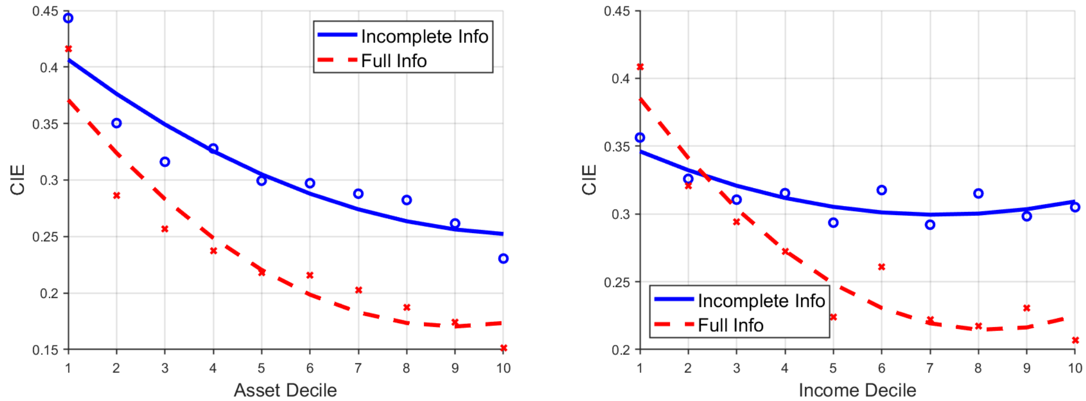
(b) Assets

Figure 16: Impulse Responses to an Idiosyncratic Income Shock - Unemployment Risk Model

Notes: Impulse response functions are calculated by subjecting a household to a one standard deviation idiosyncratic income shock, and comparing it with a counterfactual household receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.

So far we have shown that in an extension where there is unemployment risk and where agents obtain noisy signals about separation and job-finding rates we still observe excess consumption volatility under incomplete information. The last result that we revisit is the low or nonexistent correlation between household consumption elasticities and income, which was a central prediction of our baseline model. Figure 17 presents the consumption elasticities to aggregate income under the presence of unemployment risk.[30]

[30] We follow the same methodology described in Section 3.2.3 to generate these results.



(a) Elasticities by Wealth

(b) Elasticities by Income

Figure 17: Consumption-Income Elasticities to Aggregate Income - Unemployment Risk Model

Notes: The solid and dashed curves are fit from quadratic regressions. The distributions of CIE^G are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate, idiosyncratic and unemployment shocks for both models. The elasticity is calculated at the household level and averaged within household groups corresponding to the asset or income deciles of the incomplete information model's ergodic distribution. Households are grouped based on their position in period $t-1$ for a shock that occurs in period t. The plotted elasticities only include periods with aggregate shocks exceeding two standard deviations in absolute value.

We observe that the two main features observed in Section 3.2.3 are still present: there is elevation and homogenization of the consumption elasticities to aggregate income. In particular, the average consumption elasticity under full information is 0.27 while it is 0.31 in the incomplete information case. We also see that these responses tend to be much more homogeneous across wealth and income deciles, mimicking the results observed in our baseline scenario. Finally, we see that consumption elasticities are lower than in the absence of unemployment risk, which is expected due to the additional precautionary motive generated by the risk of becoming unemployed.

Introducing unemployment risk to the baseline model changes household decisions and makes macroeconomic shocks more salient. And yet, because agents still do not have full information, the main conclusions that we obtained from the baseline model remain unchanged.

E Additional Empirical Results

In this section we run several additional empirical tests of our information friction to complement our findings from Section 5. First, we estimate that household forecasts overreact to aggregate earnings relative to the rational expectation. Then, we turn to income and consumption data from the PSID and find that consumption overreacts and underreacts similar to forecasts.

E.1 Forecast Error Overreaction Tests

Specifically, we would like to estimate the regression

$$f^y_{i,s,t} - \mathbb{E}_{i,s,t}[y_{i,s,t+1}] = \beta^{Idio} y^{Idio}_{i,s,t} + \beta^{Aggr} y^{Aggr}_{s,t} + X_{i,s,t} + \varepsilon_{i,s,t} \tag{33}$$

Again, i indexes households, s indexes their state, and t indexes the 4 month time period. $f^y_{i,s,t}$ is the household-level forecast of their 4-month-ahead earnings, $y^{Idio}_{i,s,t}$ and $y^{Aggr}_{s,t}$ are the realized aggregate and idiosyncratic earnings components, and $X_{i,s,t}$ is a vector of household-level controls. $\mathbb{E}_{i,s,t}[y_{i,s,t+1}]$ denotes the rational expectation of future income, which is unobserved. However, if the right-hand side of equation (33) is in the household's information set, then we can instead estimate the regression

$$f^y_{i,s,t} - y_{i,s,t+1} = \beta^{Idio} y^{Idio}_{i,s,t} + \beta^{Aggr} y^{Aggr}_{s,t} + X_{i,s,t} + \varepsilon_{i,s,t} - \nu_{i,s,t+1} \tag{34}$$

because the rational forecast error $\nu_{i,s,t+1} = y_{i,s,t+1} - \mathbb{E}_{i,s,t}[y_{i,s,t+1}]$ is orthogonal to everything in the time t information set. Note that the left-hand side is negative the usual forecast error that appears in regression studies such as Coibion and Gorodnichenko (2015).

In the regression model (33), the coefficients β^{Idio} and β^{Aggr} measure the *overreaction* to idiosyncratic and aggregate income components. If households have full information and

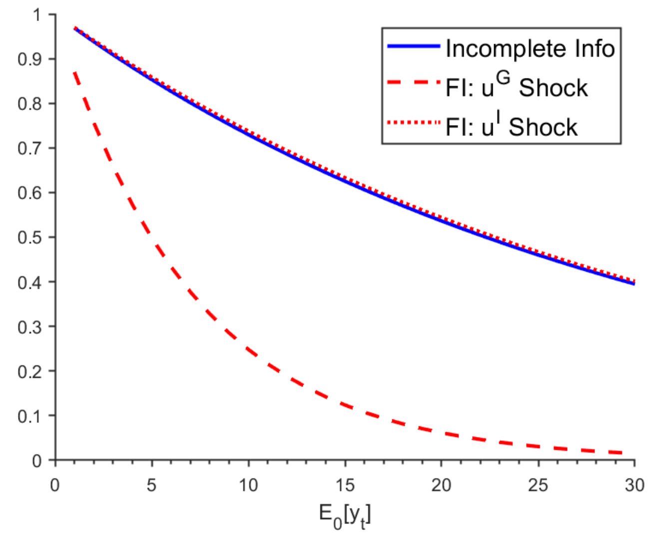


Figure 18: Relative Overreactions of Forecasts to Shocks

Notes: The figure plots the term structure of income forecasts in the baseline model. The solid blue line is the response of expectations to a unit forecast error under incomplete information, which is independent of the shock that caused it. The dashed and dotted red lines are the responses of full information expectations to aggregate and idiosyncratic shocks respectively.

rational expectations, then their values would be would be

$$\text{[FIRE]:} \qquad \beta^{Idio} = 0 \qquad \beta^{Aggr} = 0 \tag{35}$$

However, in the incomplete information model, household forecasts *overreact* to aggregate income and *underreact* to idiosyncratic income. Figure 18 demonstrates by plotting the term structure of expectations after an income shock (as in Figure 1, these are immediate term structures rather than impulse response functions.) After an aggregate shock, households forecasts overreact relative to the full information expectation. Conversely, after an idiosyncratic shock household forecasts underreact, but the underreaction is very small. This is because the variance of idiosyncratic shocks is much larger than the variance of aggregate shocks, so when household incomes change, they expect that their forecast error was mostly due to an idiosyncratic shock. In our regression model, these patterns imply $\beta^{Aggr} \gg 0$ and $\beta^{Idio} < 0$. Our main mechanism relies on the aggregate overreaction, but we also test the *relative* overreaction compared to the idiosyncratic component:

$$\text{[Incomplete Info.]:} \qquad \beta^{Idio} < \beta^{Aggr} \tag{36}$$

To do so, we perform a one-sided test against the null that β^{Idio} is larger.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Idio. Log Earnings	0.0275	0.0292	0.0443	0.109	0.102	0.108	0.109	-0.0171
	(0.0220)	(0.0221)	(0.0243)	(0.0466)	(0.0480)	(0.0468)	(0.0466)	(0.0662)
Aggr. Log Earnings	0.501	0.918	0.849	0.755	1.016	-1.806	2.901	0.447
	(0.387)	(0.564)	(0.572)	(0.810)	(0.904)	(1.858)	(1.339)	(0.844)
Lag Log Earnings				-0.0721	-0.0534		-0.0724	
				(0.0508)	(0.0760)		(0.0507)	
Lag Forecast					-0.0311			
					(0.0812)			
Lag Idio. Log Earnings						-0.0710		
						(0.0509)		
Lag Aggr. Earnings						2.730		
						(1.870)		
H_0: $\beta^{Idio} \geq \beta^{Aggr}$ p-value	0.110	0.056	0.078	0.212	0.155	0.850	0.019	0.287
Observations	7182	7182	7176	2641	2499	2641	2641	2641
R^2	0.001	0.008	0.015	0.051	0.052	0.052	0.053	0.037
State F.E.		X	X	X	X	X	X	X
Household Controls			X	X	X	X	X	X
Aggregation Level	State	State	State	State	State	State	USA	State
Regression Type	OLS	OLS	OLS	OLS	OLS	OLS	OLS	IV

Notes: Standard errors in parentheses, clustered at the state-month level. In all cases, the dependent variable is the household-level log forecast of its 4-month-ahead annualized earnings. The reported p-value is from a one-sided test with H_A: $\beta^{Idio} < \beta^{Aggr}$. In the IV regression, idiosyncratic income is instrumented for by its one period lag.

Table 12: Overreaction of Household Forecasts to Earnings Components

Table 12 presents the results of forecast regression (34). We estimated the same set of specifications as in our main regression analysis (Table 4). Column (1) is the basic regression with no additional controls; overreaction is positive but small. In column (2), we control for state-level effects on expectations. Column (3) includes the additional household-specific fixed effects discussed in Section 5. Columns (4) (matching our preferred specification from Table 4) and (5) control for additional information in households' information sets by including both lagged earnings and lagged forecasts; column (6) controls for lagged earnings components separately in case households have more information than we assume in the model. Column (7) measures the aggregate earnings component at the national rather than state level. Finally, wary of measurement error in surveyed earnings, column (8) instruments for $y^{Idio}_{i,s,t}$ with $y^{Idio}_{i,s,t-1}$.

Across nearly all specifications, we estimate overreaction to the aggregate earnings component: households make forecast errors that are predictable from macroeconomic data. The only exception is (6), where we have controlled for lags that we do not believe appear in the household's information set. Generally these tests have low power (and specification (6) has especially large standard errors), but the regressions with more observations or using aggregate shocks tend to have lower p-values. Still, the evidence is broadly consistent with our model's prediction that household forecasts overreact to aggregate earnings *relative* to idiosyncratic earnings.

We do not find evidence that households underreact to idiosyncratic income however. The estimates of β^{Idio} are near zero, but usually positive. The small coefficients match our model, but the signs do not (except in specification (8)). However this behavior is consistent with other findings that individuals' forecasts generally tend to overreact to information (Bordalo et al., 2022). If we were to extend the model such that agents had diagnostic expectations or another behavioral alternative used to fit these well-known patterns, they could display this type of modest overreaction to idiosyncratic earnings. For this reason, we focus on the relative overreaction to aggregate versus idiosyncratic components, which supports the main mechanism of the model.

E.2 Supporting Evidence from the PSID

This section employs panel data on consumption and earnings from the PSID to test the model's predictions for consumption reactions and its assumptions about idiosyncratic income persistence.

E.2.1 Consumption Evidence

The model's predictions are less clean for consumption, for which we are missing any number of relevant mechanisms, and the data are poorer, which is why our main tests focus on forecasts. But the simple model does imply similar behavior for consumption as it does for expectations: under full information, consumption should be more elastic to idiosyncratic than aggregate shocks, but under incomplete information the elasticities should be similar.

We can apply our tests from Section 5 to consumption data by estimating the regression

$$c_{i,s,t} = \beta^{Idio} y_{i,s,t}^{Idio} + \beta^{Aggr} y_{s,t}^{Aggr} + X_{i,s,t} + \varepsilon_{i,s,t} \tag{37}$$

where i indexes households, s indexes their state, and t indexes the time period. $c_{i,s,t}$ is the household-level consumption, $y_{i,s,t}^{Idio}$ and $y_{s,t}^{Aggr}$ are the realized aggregate and idiosyncratic earnings components, and $X_{i,s,t}$ is a vector of household-level controls. As before, we perform a one-sided test with the alternative hypothesis that β^{Aggr} is *larger* than β^{Idio}. If we reject $\beta^{Idio} > \beta^{Aggr}$, then we conclude that FIRE fails in a way that supports our mechanism.

We estimate regression (37) using data from the PSID. Constructing a consumption series from the PSID is nontrivial, so we adopt the consumption and wealth series constructed by Arellano et al. (2023) for heads of dual-earning households. Our only deviation from their baseline is that we use the pre-tax labor earnings series in order to match the rest of our analysis in the paper. This consumption series begins in 2005 when the PSID's expenditure questions were expanded and runs every two years to 2017.

When testing the consumption data, we make two changes relative to our forecast tests in Section 5. First, we add controls for wealth, to most closely map the consumption decision in our model. Second, we follow the standard approach when using the PSID and remove a transitory component (such as measurement error) from idiosyncratic earnings; we do this by instrumenting the current idiosyncratic earnings component with the previous period's observation.[31]

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Idio. Log Earnings	0.417	0.386	0.348	0.329	0.238	0.326	0.130	0.325
	(0.0112)	(0.0132)	(0.0141)	(0.0154)	(0.0112)	(0.0153)	(0.0139)	(0.0151)
Aggr. Log Earnings	0.602	0.527	0.506	0.443	0.334	0.721	0.265	0.216
	(0.163)	(0.172)	(0.110)	(0.113)	(0.110)	(0.118)	(0.111)	(0.111)
Log Wealth		0.0232	0.0363	0.0342	0.0445	0.0354	0.0173	0.0353
		(0.00472)	(0.00462)	(0.00494)	(0.00425)	(0.00491)	(0.00398)	(0.00492)
Lag Aggr. Earnings						-0.494		
						(0.114)		
Lag Consumption							0.572	
							(0.0112)	
H_0: $\beta^{Idio} \geq \beta^{Aggr}$ p-value	0.126	0.202	0.073	0.151	0.189	0.000	0.108	0.158
Observations	6652	6652	6652	6652	7554	6652	6652	6652
R^2	0.183	0.195	0.257	0.275	0.289	0.277	0.526	0.274
State F.E.			X	X	X	X	X	X
Household Controls				X	X	X	X	X
Aggregation Level	State	State	State	State	State	State	State	USA
Regression Type	IV	IV	IV	IV	OLS	IV	IV	IV

Notes: Standard errors in parentheses, clustered at the state-year level. In all cases, the dependent variable is the household-level consumption. The reported p-value is from a one-sided test with H_A: $\beta^{Idio} < \beta^{Aggr}$. In IV regressions, idiosyncratic income is instrumented for by its one period lag.

Table 13: Response of Household Consumption to Earnings Components

Table 13 presents the results of forecast regression (37). We estimated a similar set of specifications as in our main regression analysis (Table 4). Column (1) is the basic regression with no additional controls; column (2) adds a wealth control, and column (3) adds state-level effects on expectations. Our preferred specification is column (4), which includes the additional household-specific controls for education, race, and age. Column (5) estimates the

[31] This is approach is similar to that of Heathcote et al. (2010), who also model observed earnings in the PSID as the sum of an i.i.d. transitory shock and a persistent AR(1) component. They identify the persistence parameter using the relationship between first and second autocorrelations, which is the same as our IV estimator absent any additional controls.

previous specification by OLS instead of instrumenting for idiosyncratic income. Because of the IV approach, we cannot include lagged income as an information control in the same way as in the forecast tests, but column (6) adds a control for lagged aggregate earnings while column (7) adds a control for lagged consumption. Finally, column (8) measures the aggregate earnings component at the national rather than state level.

Across nearly all specifications, consumption is more elastic to aggregate earnings relative to idiosyncratic earnings. The only exception is when we use national aggregate shocks instead of state aggregate shocks. P-values are higher than in our forecast regressions, but we broadly consistent with our conclusions from those tests: households are at least as elastic to aggregate earnings as idiosyncratic earnings, contrary to our model's full information prediction. We conclude that the consumption overreactions provide evidence in support of the mechanism implied by our information friction.

E.2.2 Income Evidence

Our baseline calibration assumed that the autocorrelation of the idiosyncratic earnings component was $\rho_I = 0.97$, the value found by Guvenen et al. (2021) using administrative data on the population of workers. We view this as the most trustworthy estimate in the literature, but we can still compare it to the autocorrelation implied by the PSID data. We do so in this section, and find comparable numbers to Guvenen et al. (2021), as well as to Heathcote et al. (2010) who perform similar estimation using the PSID and also find $\rho_I = 0.97$.

We estimate the following panel regression:

$$y^{Idio}_{i,s,t} = \rho^{Idio} y^{Idio}_{i,s,t-1} + X_{i,s,t} + \varepsilon_{i,s,t}$$

for household i, instate s, at time t. $y^{Idio}_{i,s,t}$ is the idiosyncratic component of earnings and $X_{i,s,t}$ are the same household and state-specific controls employed in Section E.2.1. As in the last section, we use the PSID panel series of pre-tax labor earnings, consumption, and wealth constructed by Arellano et al. (2023). To construct the idiosyncratic component, we subtract state-level earnings from the national accounts. On the right-hand side, $y^{Idio}_{i,s,t-1}$ is instrumented with $y^{Idio}_{i,s,t-2}$ to remove purely transitory components such as measurement error.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Idio. Log Earnings	0.951 (0.0127)	0.960 (0.0143)	0.958 (0.0157)	0.938 (0.0178)	0.739 (0.0143)	0.928 (0.0201)	0.940 (0.0176)
Log Wealth		-0.00707 (0.00421)	-0.00817 (0.00439)	-0.00246 (0.00479)	0.0234 (0.00396)	-0.00322 (0.00478)	-0.00336 (0.00478)
Lag Consumption						0.0284 (0.0125)	
Observations	6511	6511	6511	6511	9084	6511	6511
R^2	0.642	0.640	0.643	0.651	0.657	0.654	0.663
State F.E.			X	X	X	X	X
Household Controls				X	X	X	X
Aggregation Level	State	State	State	State	State	State	USA
Regression Type	IV	IV	IV	IV	OLS	IV	IV

Notes: Standard errors in parentheses, clustered at the state-year level. In all cases, the dependent variable is the household-level consumption. In IV regressions, idiosyncratic income is instrumented for by its one period lag.

Table 14: Persistence of Household Idiosyncratic Earnings

Table 14 reports our estimates for several specifications from our consumption tests. Column (1) is simply a regression of earnings on lag earnings, instrumented with an additional lag, column (2) adds wealth controls, and column (3) adds state fixed effects. Our preferred specification in column (4) adds the remaining household controls, while column (5) estimates this specification by OLS. Column (6) also controls for lagged consumption, and column (7) constructs the idiosyncratic component by removing national rather than state-level earnings.

We broadly find results consistent with the values estimated by Heathcote et al. (2010) and Guvenen et al. (2021). Note that the PSID waves are every two years, so an annual autocorrelation of 0.97 would imply a biannual 0.94 autocorrelation, which is close to our results. Only the OLS regression finds a lower autocorrelation, reflecting the necessary long history of removing transitory elements from household-reported earnings in the PSID.[32] We confirm that the idiosyncratic component of income is substantially more persistent than the aggregate component that we estimated in Appendix A.

E.2.3 Consumption-Income Elasticities in the United States

In this section, we estimate the consumption elasticity to aggregate income, defined in equation (6). Similar to GOP, we estimate the CIE_d^G by income decile d. However, our estimation approach must differ. GOP measure consumption and income changes around large unexpected economic crises in four small open economies, and attribute the effects to large aggregate shocks; however this approach is not possible in the US.[33] Instead, we estimate decile-by-decile how consumption changes respond to aggregate income changes. Specifically, we estimate for each decile d

$$c_{i,s,t} - c_{i,s,t-1} = \beta_d^{CIE}(y_{s,t}^{Aggr} - y_{s,t-1}^{Aggr}) + X_{i,s,t} + \varepsilon_{i,s,t} \tag{38}$$

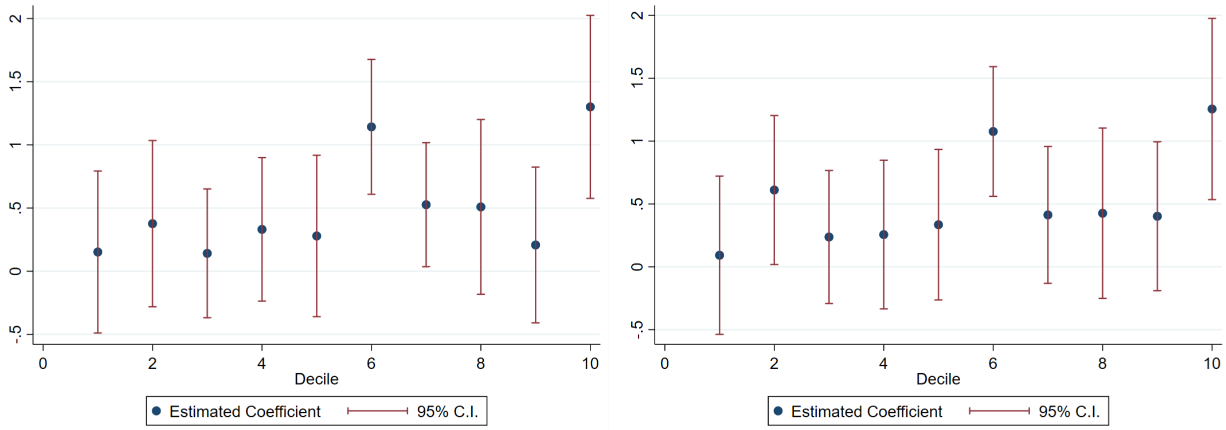
for households in income decile d in time period $t-1$. $c_{i,s,t}$ denotes detrended log consumption of household i in state$s$ at time t, $y_{s,t}^{Aggr}$ denotes the aggregate component of income in state s at time t, and $X_{i,s,t}$ is a vector of controls.

We estimate the CIE_d^G as the coefficient β_d^{CIE}. This requires panel data on consumption, so again we employ the Arellano et al. (2023) consumption measure using the PSID. Data for our regression begin in 2005 and appear biannually through 2017. Each decile regression has on average 665 observations. As before, aggregate earnings is measured at the state level using the national accounts, and both log income and log consumption are detrended using

[32] To be consistent, we also perform our aggregate persistence estimation with the same IV approach, and it does not change our conclusions (Table 7).

[33] The closest analog for the US is the 2008 financial crisis, but restricting the PSID sample to changes around this year would leave us with only about 120 observations of consumption changes per decile. When we explored this option, many estimates were nonsensically large or negative, with massive standard errors.

quadratic trends that are the same across households.



(a) Specification with Household Controls

(b) Simple Specification

Figure 19: Estimated Consumption-Income Elasticities by Income Decile

Notes: The figure reports estimates of the Consumption-Income Elasticities to Aggregate Income in the US. Each panel plots the estimated coefficient β_d^{CIE} from regression (38) by income decile, and the associated 95% confidence intervals clustered at the state-year level. Panel (a) controls for household characteristics: education, race, age, and state. Panel (b) includes no additional controls.

Figure 19 reports the estimates of β_d^{CIE} by decile, and the 95% confidence intervals based on standard errors clustered at the state-year level. Panel (a) includes controls for education, race, and age of the household's main earner, as well as state fixed effects. Panel (b) reports the simplest specification without any additional controls beyond a common constant. In both cases, the average value of β_d^{CIE} across deciles is large (0.51 in panel (a) and 0.49 in panel (b)) and increasing in income. This result is qualitatively consistent with the GOP findings.

We view this exercise as a corroboration that we can address the pattern that GOP for multiple countries in the context of US states. But our estimation is not a close substitute for their results for two reasons. First, the PSID suffers from substantially smaller sample sizes than any of the consumption datasets used by GOP, hampering our ability to estimate consumption responses. Second, the aggregate income changes that we study are an order of magnitude smaller than in GOP, further increasing our standard errors. And yet, uncertainty aside, our point estimates suggest that GOP's findings apply in broader settings.

F Robustness and Sensitivity Analysis

This section provides a description and results of 3 robustness analyses that we run for some of our model specifications. The first one consists of an alternative calibration for the baseline model under full information, where we recalibrate the interest rate so that the net worth to income ratio matches the one of the incomplete information model. The second analysis involves the addition of a stochastic discount factor in order to generate a better fit of the implied wealth distribution of the incomplete information model. The third robustness analysis studies how sensitive the main conclusions of the baseline model and the heterogeneous skill types extension are when varying specific parameters.

F.1 Alternative Calibration for the Baseline Model

In this section we present key results of our baseline model with an alternative calibration for the full information scenario. In particular, we adjust the interest rate in the full information case in order to match the same average net-worth-to-earnings ratio as in the incomplete information case. The required value for the full information interest rate is $r = 0.0268$, which is 68 basis points higher than under incomplete information ($r = 0.02$).

Table 15 presents the long-run moments for the full and incomplete information scenarios. Note that the moments of the incomplete information case are unaltered since we do not recalibrate any parameters. We see that the main message of Section 3.2.1 remains: under incomplete information, aggregate consumption is more volatile and less autocorrelated. Note that the gap is wider than in our baseline calibration because the larger full information interest rate induces greater savings, enabling further consumption smoothing. In terms of the cross-sectional moments, we see that the higher interest rate under full information leads to larger average assets than in our baseline (by construction). The additional asset income increases average consumption relative to incomplete information.

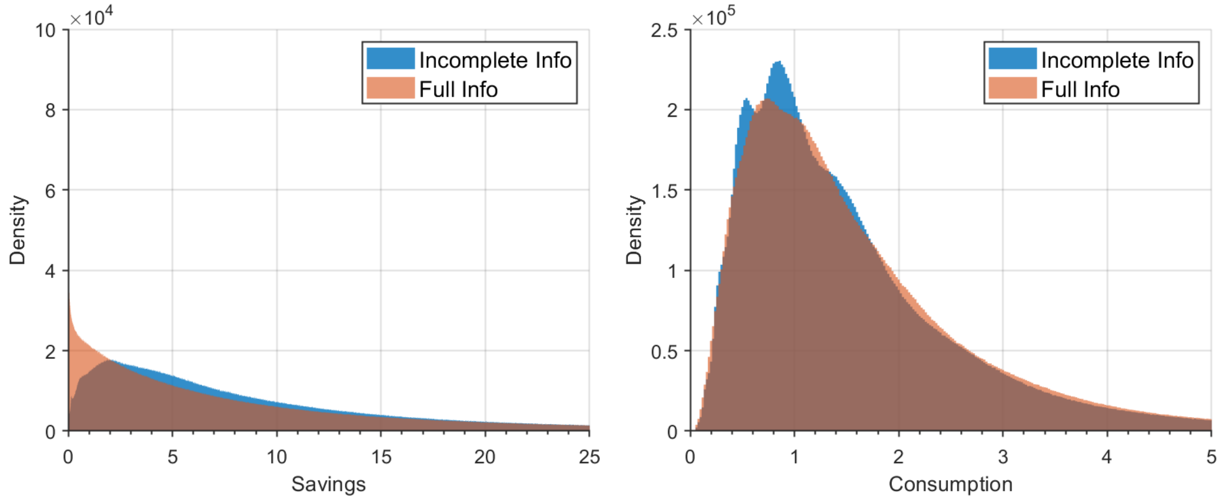
We present a selection of results that illustrate the main differences under the alternative

	Full Information	Incomplete Information
Aggregate Dynamics		
Consumption: Standard Deviation (log change)	0.0071	0.0121
Consumption: Autocorrelation	0.982	0.952
Assets: Standard Deviation (log change)	0.0052	0.0038
Assets: Autocorrelation	0.998	0.997
Cross-Sectional Statistics		
Income: Mean	1.38	1.38
Income: Coefficient of Variation	0.95	0.95
Consumption: Mean	1.67	1.60
Consumption: Coefficient of Variation	0.80	0.79
Consumption: Autocorrelation	0.989	0.99
Assets: Mean	10.65	11.06
Assets: Coefficient of Variation	1.32	1.19
Assets: Autocorrelation	1.00	1.00

Notes: Long-run moments are calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models.

Table 15: Long-run Moments - Alternative Calibration

calibration. Figure 20 presents the ergodic distributions for assets and consumption. Due to the higher interest rate, the entire consumption distribution under full information has shifted to the right compared to the baseline calibration. This shift is generated by the increase in asset and larger returns to savings.



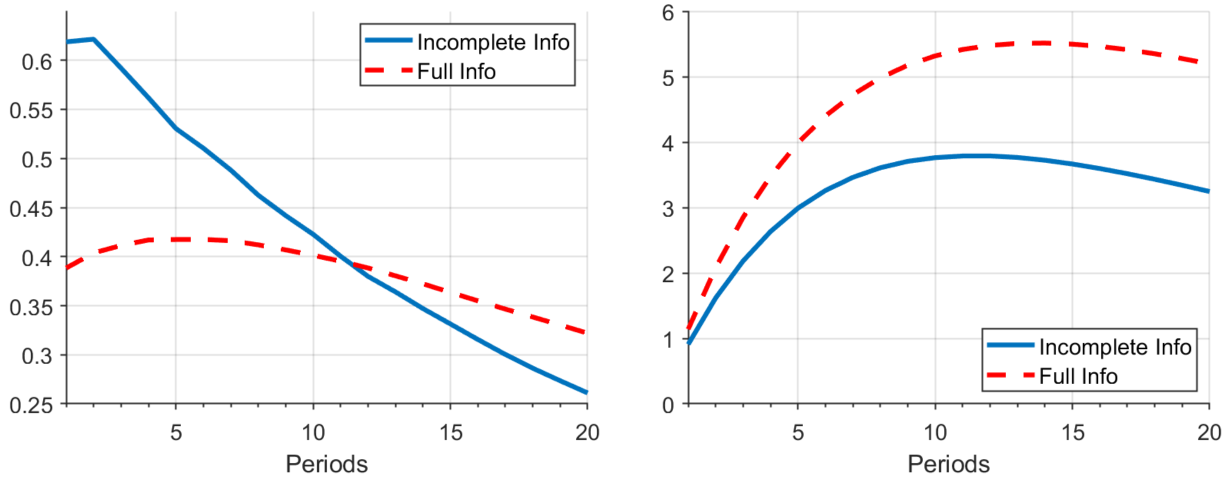
(a) Assets

(b) Consumption

Figure 20: Ergodic Distributions - Full and Incomplete Information Models - Alternative Calibration

Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. Both distributions extend outside the axis range, but the right tails are omitted for readability.

In order to better understand how the information friction exacerbates aggregate consumption volatility under the alternative calibration, Figure 21 replicates panels (a) and (b) of Figure 3 and presents impulse response functions to an aggregate shock in the new approach. Overall, we see little change in the dynamics of aggregate consumption and assets in response to an aggregate shock, under full information. This is consistent with what we found in Table 15. For completeness, we also present the dynamics of aggregate consumption and assets in response to an idiosyncratic, which are summarized in Figure 22. The results do not vary substantially with respect to the baseline calibration.

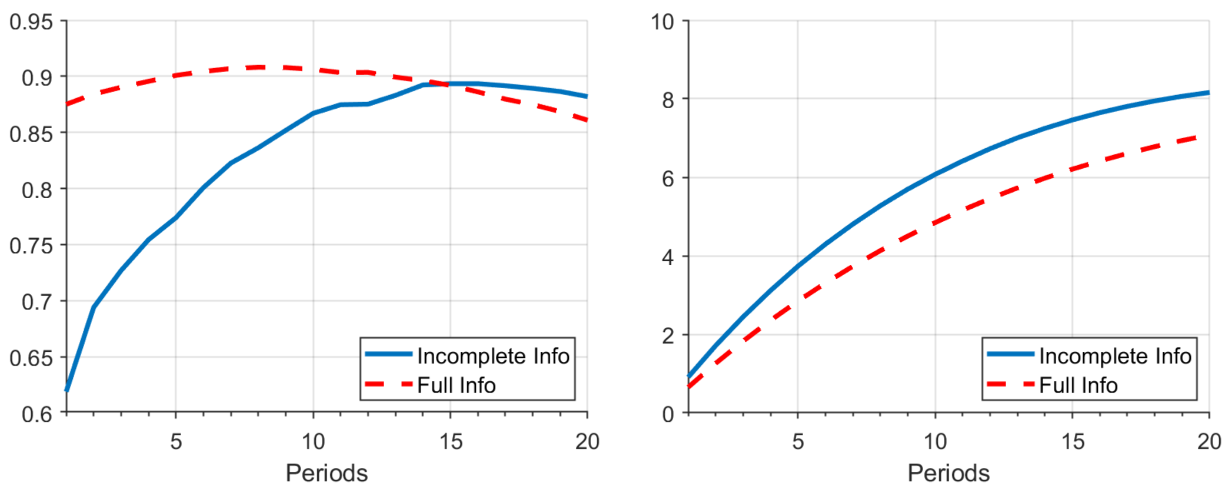


(a) Consumption

(b) Assets

Figure 21: Impulse Responses to an Aggregate Income Shock - Alternative Calibration

Notes: Impulse response functions are calculated by subjecting the economy to a one standard deviation aggregate income shock and comparing with a counterfactual economy receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.



(a) Consumption

(b) Assets

Figure 22: Impulse Responses to an Idiosyncratic Income Shock - Alternative Calibration

Notes: Impulse response functions are calculated by subjecting a household to a one standard deviation idiosyncratic income shock and comparing it with a counterfactual household receiving no shock. The impulse response functions are reported as the difference in consumption or assets, normalized by the size of the shock.

Lastly, we compute the consumption-income elasticities under the alternative calibration. Figure 23 presents the ergodic distribution of this object while Figure 24 presents the consumption-income elasticities to aggregate shocks.

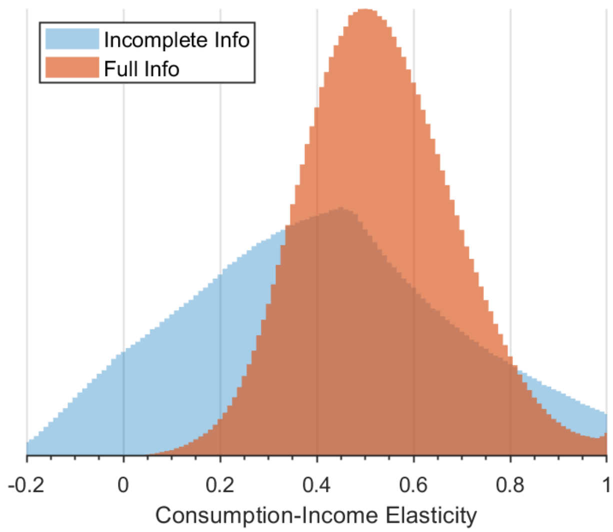
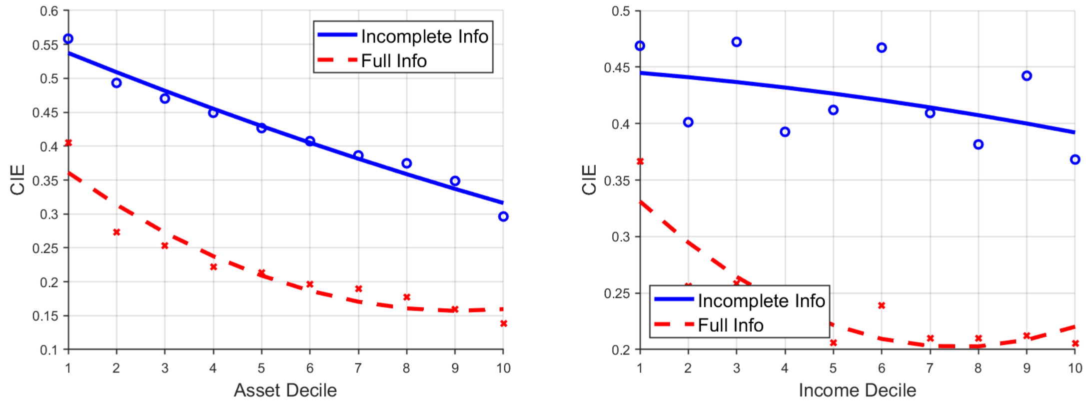


Figure 23: Ergodic Distributions of Consumption-Income Elasticities - Alternative Calibration

Notes: The ergodic distributions of household-level CIEs are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. CIEs in the plotted distributions are only included for households experiencing income changes of one standard deviation or more in absolute value.



(a) Elasticities by Wealth (b) Elasticities by Income

Figure 24: Consumption-Income Elasticities to Aggregate Income - Alternative Calibration

Notes: The solid and dashed curves are fit from quadratic regressions. The distributions of CIE^G are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. The elasticity is calculated at the household level and averaged within household groups corresponding to the asset or income deciles of the incomplete information model's ergodic distribution. Households are grouped based on their position in period $t-1$ for a shock that occurs in period t. The plotted elasticities only include periods with aggregate shocks exceeding two standard deviations in absolute value.

The same patterns remain: CIEs are higher, on average, and relatively homogeneous in response to aggregate shocks under incomplete information. This alternative calibration targeting full information wealth instead of the interest rate does not affect our main conclusions

F.2 Stochastic Discount Factor & Wealth Distributions

The purpose of this extension is to provide a simple framework with incomplete information that can generate wealth distributions closer US data. We assume that the households' discount factor is stochastic. The discount factor takes values from a grid $\{\bar{\beta}-\kappa, \bar{\beta}, \bar{\beta}+\kappa\}$ and has a transition probability matrix P^{β}, following Krusell and Smith (1998). We calibrate κ and $\bar{\beta}$ so that the wealth distribution of the extended incomplete information model replicates the wealth gini coefficient of the US according to (0.77, as estimated by Krueger et al., 2016) and where the asset-to-income ratio is roughly 8. We set both parameters to be $\kappa = 0.109$

and $\bar{\beta} = 0.89$. P^{β} is set according to Krusell and Smith (1998):

$$P^{\beta} = \begin{bmatrix} 0.995 & 0.005 & 0 \\ 0.000625 & 0.99875 & 0.000625 \\ 0 & 0.005 & 0.995 \end{bmatrix}$$

Our model now features an additional exogenous state, the discount factor. The calibration of the model is identical to the one presented in Section 3.1 except for the discount factor. The solution method is the same as the one documented in Section C.1 with a minor modification in terms of how expectations are computed.[34]

Table 16 presents the distributional moments (fraction of wealth holdings by wealth quintiles) of both models (baseline and the stochastic discount factor variant) and their empirical counterparts. The empirical measures correspond to the ones reported in Krueger et al. (2016), which are generated from the PSID and the SCF.

% Share	Model		Data	
by:	Baseline	SDF	PSID	SCF (2007)
Q_1	2.7	0.7	-0.9	-0.2
Q_2	7.1	2.2	0.8	1.2
Q_3	12.6	4.8	4.4	4.6
Q_4	21.9	10.4	13	11.9
Q_5	55.7	81.9	82.7	82.5

Table 16: Distributional Moments

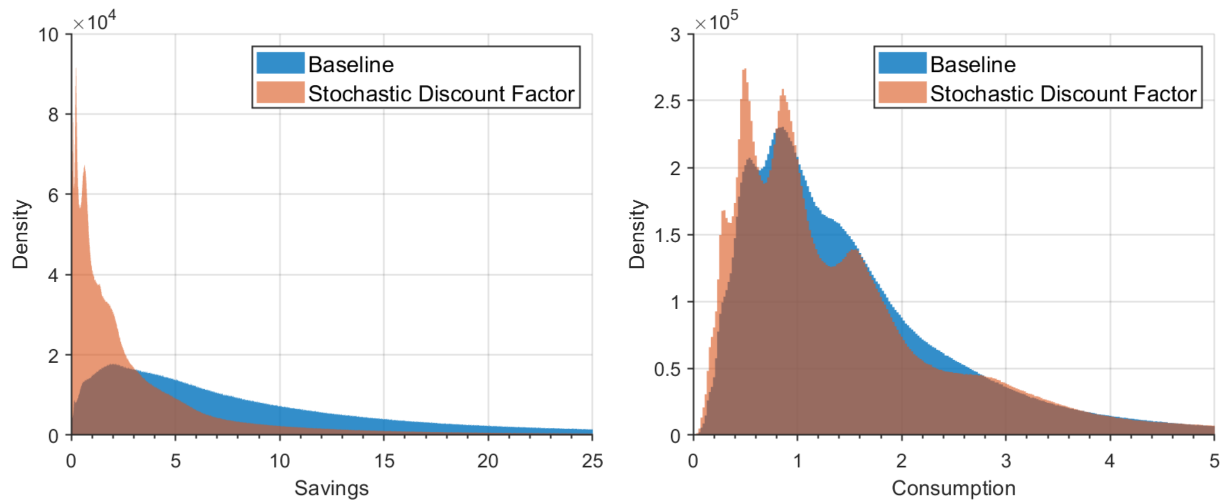
Notes: Table 16 presents the distribution (in percent) of wealth holdings according to wealth quintiles. Baseline stands for the baseline model under incomplete information. SDF stands for the variant of the incomplete information model with a stochastic discount factor. The data column corresponds to the empirical counterparts observed in the PSID and SCF, as reported in Krueger et al. (2016).

The baseline scenario, illustrated in column 2 of Table 16, shows that the predicted shares of asset holdings across the wealth distribution are quite distant from the data. When introducing the stochastic discount factor we observe a drastic improvement in the first of the distribution of asset holdings relative to its empirical counterpart. In particular, we see that

[34]In the incomplete information setting, the number of grid points associated with exogenous states now rises to 3993 ($11 \times 11 \times 11 \times 3$).

the incomplete information model can match reasonably well the asset holdings distribution, despite it not being a target of the calibration.

Figure 25 presents the ergodic distributions for assets and consumption across models. We see that with a stochastic discount factor, the asset ergodic distribution has substantially more mass towards very low asset holdings. This is due to the presence of impatient agents, whose low savings are not compensated by the very patient ones. Due to lower asset holdings, we also see that the consumption ergodic distribution is slightly shifted to the left of the baseline one.



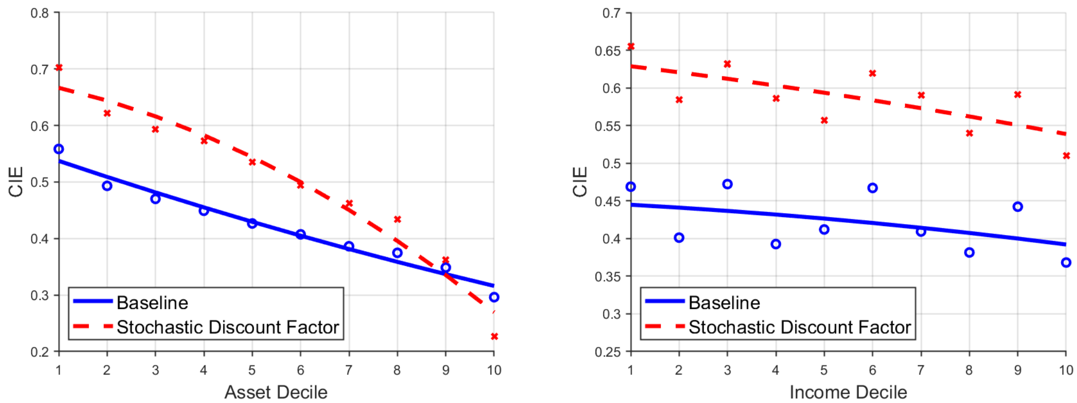
(a) Assets

(b) Consumption

Figure 25: Ergodic Distributions - Baseline vs. Stochastic Discount Factor Model

Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. Both distributions extend outside the axis range, but the right tails are omitted for readability.

Is the result of elevation and homogenization of consumption-income elasticities under incomplete information still a feature in this variation? The answer is shown in the figures below. Figure 26 presents the CIEs to an aggregate income shock. Interestingly, we see that the CIE to aggregate income is larger when we introduce the stochastic discount factor, but it maintains the same homogeneous (or flat) behavior across income deciles. Thus, one of the main results of our baseline model remains in this model variation.



(a) Elasticities by Wealth

(b) Elasticities by Income

Figure 26: Consumption-Income Elasticities to Aggregate Income - Stochastic Discount Factor

Notes: The solid and dashed curves are fit from quadratic regressions. The distributions of CIE^G are each calculated from a simulation of 2,000 households and 10,000 periods. We use the same sequences of aggregate and idiosyncratic shocks for both models. The elasticity is calculated at the household level and averaged within household groups corresponding to the asset or income deciles of the baseline incomplete information model's ergodic distribution. Households are grouped based on their position in period $t-1$ for a shock that occurs in period t. The plotted elasticities only include periods with aggregate shocks exceeding two standard deviations in absolute value.

F.3 Parameter Sensitivity Analysis

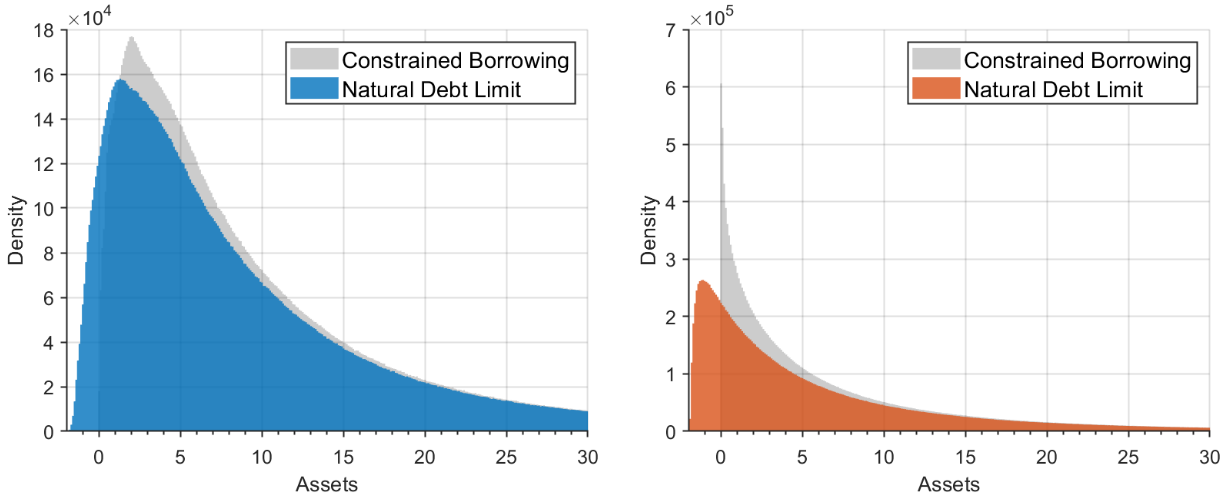
F.3.1 The Borrowing Constraint

To ascertain the impact of the financial friction on our economy, we solve the model for several values of the borrowing constraint, ranging from the no-borrowing baseline to the natural borrowing limit.[35]

Figure 27 plots asset distributions under incomplete and full information for each of these two extreme values. In both cases, reducing the lower bound on assets weakens the distortion that precautionary savings has on the asset distribution: the distribution shifts left of zero, with large masses of agents borrowing to smooth income shocks.

However, this effect is asymmetric across information structures. Under incomplete infor-

[35] The natural borrowing limit is $-\bar{A} = y_{\min}/r$, where $y_{\min}$ denotes the lowest possible value in the income grid, which in logs is roughly -4 standard deviations. We construct the income grids to imply the same natural borrowing limit for both models.



(a) Incomplete Information (b) Full Information

Figure 27: Ergodic Distribution of Assets with the Natural Borrowing Limit

Notes: The ergodic distributions are each calculated from a simulation of 2,000 households and 10,000 periods, experiencing the same sequences of aggregate and idiosyncratic shocks. The light gray distributions are the corresponding ergodic distributions when no borrowing is allowed (Figure 2).

mation, households' rational forecasts are relatively inaccurate; the variance of their income forecast error $w_{i,t}$ is strictly larger than under full information, because $w_{i,t}$ is affected by the same contemporaneous shocks in addition to a linear combination of past shocks (Appendix B.1). This perceived riskiness strengthens their precautionary savings motive. Therefore few of them choose to be constrained even when unable to borrow, and so relaxing the constraint has little effect on the distribution of assets. Conversely, full information households have a weaker precautionary savings motive, often choosing to go to the constraint. When the constraint is relaxed, many more households borrow than under incomplete information.

Therefore, we conclude that the information friction interacts to attenuate the financial friction. By raising the precautionary savings motive, the information friction makes the borrowing constraint less distortionary.

F.3.2 Idiosyncratic Risk

How does the economy change when we adjust the dynamics of idiosyncratic income risk? To address this question, we consider alternative values of ρ_I, the autocorrelation on the idiosyncratic component of income Y^I. This parameter has no effect on how full information agents forecast aggregate income, but under incomplete information, increasing ρ_I makes forecasting aggregate income more difficult by making the combined income process more persistent (as demonstrated in Figure 1.) Figure 28 plots several summary statistics for a range of values of ρ_I.

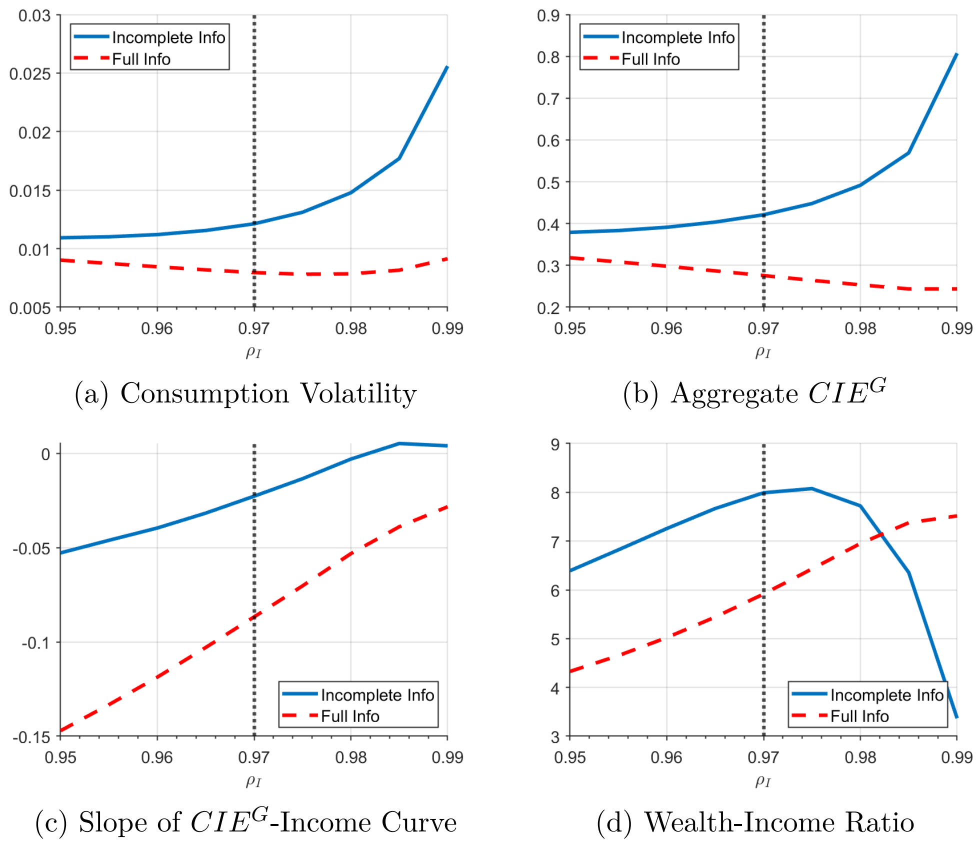


Figure 28: Sensitivity to Idiosyncratic Persistence

Notes: We consider the same sequence of shocks for both models, for every possible value of ρ_I. The baseline $\rho_I = 0.97$ is marked with a dotted line in each panel. Each statistic is calculated from a simulation of 2,000 households and 10,000 periods, experiencing the same sequences of aggregate and idiosyncratic shocks.

When idiosyncratic income is more persistent, households increasingly mistake aggregate shocks for permanent income shocks. This strengthens the main mechanisms of our model. Increasing ρ_I raises aggregate consumption volatility (Figure 28 panel (a)) and raises consumption elasticities to aggregate income (panel (b)). Increasing ρ_I also increases the homogenization effect documented by GOP: the slope of the CIE^G-income relationship rises (panel (c)). If idiosyncratic income is sufficiently persistent, the slope can become positive. GOP document a positive relationship for several countries, but this never occurs in our full information model.

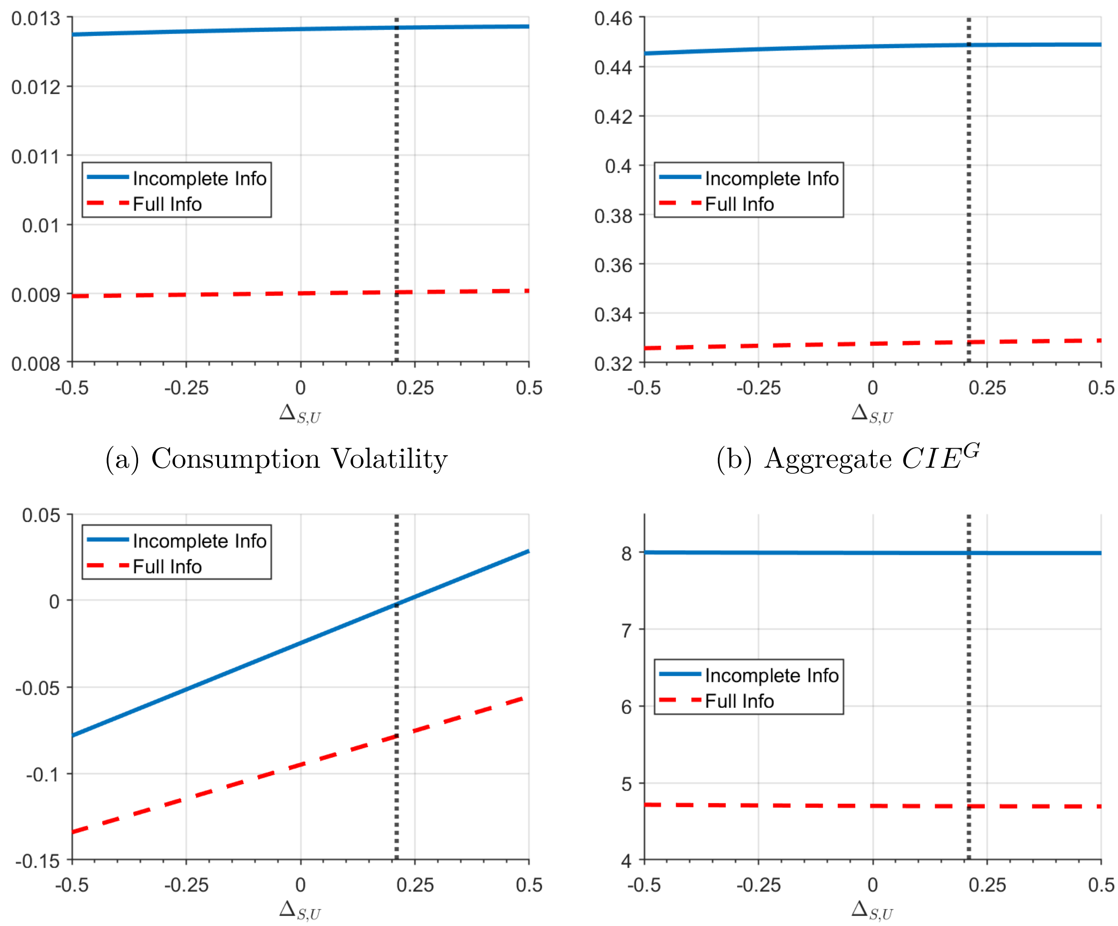
The autocorrelation ρ_I has a nonmonotonic effect on the precautionary savings motive. Panel (d) makes this clear, plotting the ratio of average wealth to average income. At most levels, increasing ρ_I increases household income risk. However, when idiosyncratic income becomes extremely persistent, the precautionary savings motive weakens. For intuition, consider the limit: when income shocks are completely permanent, there is no precautionary savings motive at all, because consumption follows income one-for-one.

These effects are not common across information structures. The full information CIE^G is decreasing in ρ_I, while it rises under incomplete information. Why? Under full information, the CIE^G moves inversely to the wealth-income ratio, because households consume more when they hold greater wealth, so their consumption is less elastic to aggregate income shocks. The information friction breaks this relationship: when information is incomplete, ρ_I monotonically increases the CIE^G. Under both information structures, a larger ρ_I makes consumption more elastic to idiosyncratic income shocks. But with the friction, households cannot distinguish aggregate from idiosyncratic shocks, so their consumption choice must be more elastic to both types of shocks.

F.3.3 Heterogeneous Skill Types

The elasticity difference across skill types $\Delta_{S,U} \equiv \alpha_S^G - \alpha_U^G$ is a crucial parameter in our heterogeneous skill type extension. Because of this, we provide a robustness analysis to assess how key moments related to the main predictions of the model vary whenever we vary this parameter.

In our calibration of the model with heterogeneous skill types, we set $\Delta_{S,U} = 0.21$. We now consider a wider range of values that $\Delta_{S,U}$ can take. In particular, we allow $\Delta_{S,U} \in [-0.5, 0.5]$. Negative values of $\Delta_{S,U}$ imply that the income of the unskilled is *more* sensitive to aggregate income fluctuations relative to skilled agents, while for positive values the opposite occurs. Figure 29 presents how consumption volatility, the average CIE^G, the slope of CIE^G, and the wealth-to-income ratio vary whenever we vary $\Delta_{S,U}$.



(a) Consumption Volatility

(b) Aggregate CIE^G

(c) Slope of CIE^G-Income Curve

(d) Wealth-Income Ratio

Figure 29: Sensitivity to Skill Premium Elasticity Gap $\Delta_{S,U}$

Notes: We consider the same sequence of shocks for both models, for every possible value of the skill premium elasticity gap between skilled and unskilled types. The baseline $\Delta_{S,U} = 0.21$ is marked with a dotted line in each panel. Each statistic is calculated from a simulation of 2,000 households and 10,000 periods, experiencing the same sequences of aggregate and idiosyncratic shocks.

Our sensitivity analysis shows that consumption volatility does not vary importantly for most of the values of $\Delta_{S,U}$ that we consider. The same happens for the aggregate CIE^G and the average wealth-to-income ratio.

We do observe that the slope of the CIE^G-income curve is sensitive to $\Delta_{S,U}$. The mechanism is straightforward: when unskilled lower earning households are more sensitive to aggregate shocks, then low income households also have consumption that is more elastic to aggregate shocks. Regardless, for all values of $\Delta_{S,U}$, the slope is consistently more positive under incomplete information than full information.

To conclude, the robustness analysis of different skill premium elasticity gaps shows that the main conclusions of the heterogeneous skill types extension do not change importantly whenever varying this important parameter. We still observe that consumption is more volatile (panel (a)) due to oversaving under incomplete information (panel (d)), and there is an elevation (panel (b)) and homogenization (panel (c)) of the consumption elasticity to aggregate income shocks.

G Proof of Proposition 1

Proof. Let $\Omega_{i,s,t}$ denote the information set of household i in state s at time t. Its FIRE forecast is

$$f^y_{i,s,t} = \mathbb{E}[y_{i,s,t+1}|\Omega_{i,s,t}] = \mathbb{E}[y^{Idio}_{i,s,t+1}|\Omega_{i,s,t}] + \mathbb{E}[y^{Aggr}_{s,t+1}|\Omega_{i,s,t}]$$

The household's information set $\Omega_{i,s,t}$ includes the history of income components, as well as possible information informing their forecasts of $u^{Idio}_{i,s,t+1}$ and $u^{Aggr}_{s,t+1}$. Plug in with equation (8):

$$= \sum_{k=1}^{\infty} \rho^{Idio}_k y^{Idio}_{i,s,t+1-k} + \mathbb{E}[u^{Idio}_{i,s,t+1}|\Omega_{i,s,t}] + \sum_{k=1}^{\infty} \rho^{Aggr}_k y^{Aggr}_{i,s,t+1-k} + \mathbb{E}_t[u^{Aggr}_{s,t+1}|\Omega_{i,s,t}]$$

Thus, if all income component lags with non-zero coefficients are included in $X_{i,s,t}$, then β^{Aggr} and β^{Idio} will match ρ^{Idio}_1 and ρ^{Aggr}_1 in Equation (7) if the news term $\mathbb{E}[u^{Idio}_{i,s,t+1}|\Omega_{i,s,t}] +$

$\mathbb{E}_t[u^{Aggr}_{s,t+1}|\Omega_{i,s,t}]$ is orthogonal to the income components. This is necessarily true because $u^{Idio}_{i,s,t+1}$ is orthogonal to $\{y^{Idio}_{i,s,t-k}\}^{\infty}_{k=0}$, $u^{Aggr}_{s,t+1}$ is orthogonal to $\{y^{Aggr}_{s,t-k}\}^{\infty}_{k=0}$, and all idiosyncratic terms are orthogonal to all aggregate terms by definition. ■