Consumption Wedges:
Measuring and Diagnosing Distortions [*]

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Abstract

Deviations from canonical consumption-savings models have been attributed to a wide range of distortions, including financial constraints and behavioral preferences. We develop a new sufficient statistics approach to measure the impact of such distortions on consumption as a *micro-level wedge* between actual consumption and a counterfactual "frictionless" consumption. Our approach is applicable to a broad class of models and, unlike standard wedge measurement approaches, does not rely on an assumption of full-information rational expectations (FIRE), which allows us to isolate the influence of frictions and behavioral preferences from deviations from FIRE. Since different frictions imply different properties of wedges, the estimates of wedges can be used as a diagnostic to distinguish between models. To implement this approach, we field a new survey of economic beliefs, which we link to bank account transactions data for a population of predominantly middle-income US consumers with low liquid wealth. We find that consumption choices are significantly distorted both upward and downward. The median wedge is 40% of frictionless consumption in absolute value, with 49% of consumers having negative wedges (under-consuming) and 51% having positive wedges (over-consuming). Since financial constraints only generate negative wedges, additional or alternative distortions (such as present bias or consumer inertia) are necessary to rationalize the consumption decisions of low-liquidity households.

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1 Introduction

Financial constraints play a central role in theories of consumption-savings behavior in macroeconomics and household finance (e.g., Kaplan and Violante, 2014). A key motivation for the focus on financial constraints is extensive empirical evidence of deviations from the permanent income hypothesis, such as high marginal propensities to consume (MPCs) out of transitory income changes, especially among households with low liquid wealth (e.g., Johnson, Parker and Souleles, 2006).[1] However, alternative distortions—such as present bias, consumption adjustment costs, and bounded rationality—can also account for these empirical patterns (Lee and Maxted, 2023; Maxted, Laibson and Moll, 2024; Beraja and Zorzi, 2024; Ilut and Valchev, 2023). Importantly, these alternative models imply different distributional and aggregate consequences of fiscal policy, monetary policy, and business cycle fluctuations.[2] To better guide theory and ultimately policy, more evidence is needed on which distortions influence consumption and by how much.

We develop a new sufficient statistics approach to measure the household-level impact of distortions as *consumption wedges* between actual consumption and a counterfactual "frictionless" consumption. Consumption wedges quantify the total impact of distortions on consumption, including both frictions (such as borrowing constraints) and behavioral preferences that result in "as if" constrained behavior (e.g., present bias or bounded rationality). Because alternative distortions have different predictions for the properties of consumption wedges—such as their signs, correlates, and responses to shocks—they can be used as a diagnostic to discriminate between models of consumer behavior. Unlike existing wedge-based analyses (e.g., Chari, Kehoe and McGrattan, 2007; Berger, Bocola and Dovis, 2023), we measure wedges using subjective expectations data, which allows us to avoid assuming full-information rational expectations (FIRE) and to isolate the influence of distortions on consumption separately from the influence of deviations from FIRE. We also differ by measuring wedges at the household (micro) level rather than the aggregate (macro) level, enabling us to document heterogeneity in wedges.

We implement our approach using new data on consumer expectations linked to administrative transactions data for a population of predominantly middle-income US consumers with low liquid wealth. We find that wedges are large and exhibit substantial heterogeneity. The median *absolute value* wedge is 40% of frictionless consumption, indicating that distortions are a large determinant of consumption for low-liquidity households. Additionally, we find that 49%

[1] Other influential empirical patterns include the excess smoothness of consumption out of persistent income shocks (e.g., Campbell and Deaton, 1989; Attanasio and Pavoni, 2011) and lack of correlation between the real interest rate and expected consumption growth (e.g., Campbell and Mankiw, 1989; Attanasio and Weber, 1993).

[2] For example, Lee and Maxted (2023) shows that adding present bias to an otherwise standard heterogeneous agent New Keynesian model (which features borrowing constraints and an illiquid asset) leads to significant amplification of both fiscal and monetary policy.

of consumers have negative wedges (under-consumption) and 51% have positive wedges (over-consumption). The mix of positive and negative wedges implies that financial constraints—the primary friction used to explain high MPCs—are not the dominant distortion for at least 51% of our sample. Financial constraints can only create negative wedges, as they distort consumption downward. We identify two alternative sets of distortions that can rationalize the data: (1) a combination of present bias and financial constraints and/or (2) consumer inertia (such as consumption adjustment costs or due to bounded rationality). Taken together, our results indicate that distortions beyond financial constraints play a first-order role in shaping the consumption of low-liquidity households.

To measure wedges, we begin by characterizing frictionless consumption in a stylized model. A household chooses consumption and saving (or borrowing) via a risky asset given their realized income and wealth. Under the benchmark model, households face no frictions (borrowing constraints, consumption adjustment costs, etc.) and have standard preferences.[3] Our benchmark model allows household beliefs to flexibly deviate from FIRE. As a result, the wedge between a household's actual and "frictionless" consumption quantifies the degree to which households over- or under-consume due to any frictions or non-standard preferences, isolating their impact from the influence of any deviations from FIRE.

In the benchmark model, frictionless consumption is characterized by an Euler equation and a budget constraint. Under a first-order approximation, frictionless consumption is a function of net worth, income, and beliefs about future nominal income growth, nominal interest rates, and inflation. Our characterization relies on the Euler equation and budget constraint being necessary conditions for optimality, but they need not be sufficient. As a result, our formula for frictionless consumption is robust to a variety of model extensions, such as additional household choices (e.g., labor supply) and a richer asset environment (including the case of complete markets). We intentionally exclude frictions and behavioral preferences from our benchmark; as a result, the wedge between actual and frictionless consumption quantifies the total net impact on consumption of *all* distortions (frictions and behavioral preferences).

We measure micro-level consumption wedges using new data that link subjective expectations to administrative consumer transactions data. The transactions data come from EarnIn, an American financial technology company that offers their users early access to their wages prior to their regularly scheduled payday. The sample is not representative; notably, it skews toward middle-income households with low liquid wealth.[4] EarnIn fielded three surveys to its users be-

[3] We use the term "standard preferences" to refer to utility functions that are time consistent, time separable, strictly increasing, strictly concave, and differentiable.

[4] We later discuss implications for external validity and give guidance for using our estimates to calibrate models.

tween 2022–2024 that solicited expectations over inflation, nominal income growth, and nominal interest rates (for both saving and borrowing). We study merged data linking 5,034 respondents' de-identified transactions data to their surveyed expectations.

Eliciting subjective beliefs is important for two reasons. First, subjective expectations data enable us to avoid assuming FIRE. Prior analyses of economic wedges assume FIRE because it allows estimating rational expectations by averaging realized outcomes (e.g., Chari, Kehoe and McGrattan, 2007; Berger, Bocola and Dovis, 2023). However, behaviors that are consistent with constrained optimization can also generally be rationalized by some set of beliefs. Prior wedge analyses may therefore conflate the effects of frictions with deviations from FIRE. Our wedge analysis is the first, to our knowledge, to relax the assumption of FIRE, allowing us to quantify the impact of frictions and non-standard preferences separately from the effects of any deviations from FIRE.

The second advantage of subjective beliefs data is that it allows us to calculate individual-level rather than aggregate wedges. Even if households actually form FIRE, measuring individual-level wedges based on realized (future) individual-level outcomes would conflate the impact of frictions and behavioral preferences with prediction error. To overcome this, prior work averaged wedges across households with similar observable characteristics, and then focused on aggregate or group-level wedges (Berger et al., 2023). Subjective expectations data allow us to directly calculate individual-level wedges.

We have two main results. First, we find that the typical consumption wedge is large. In absolute value, the median wedge is 40% of frictionless consumption. The magnitude of this estimate implies that distortions are first-order determinants of consumption among low-liquidity households. Hence, incorporating frictions or behavioral preferences into theories of consumer behavior is necessary to generate a realistic cross-section of consumption. The significant cross-sectional heterogeneity also implies that frictions and/or behavioral preferences are important determinants of the distribution of welfare. And because heterogeneity in consumer behavior can matter for aggregate outcomes (e.g., Kaplan et al., 2018), this heterogeneity may also be important for explaining aggregate consumption and income. Additionally, without first taking its absolute value, the average and median wedge is much smaller (16% and 1.4% of frictionless consumption, respectively). This highlights the value of studying micro-level wedges, as aggregate or average wedges may understate the importance of frictions in the cross-section.

Second, the observed distribution of wedges rejects financial constraints as the dominant friction for at least one quarter of our sample. We find that 51% of wedges are positive (over-consumption) and 49% are negative (under-consumption). Since financial constraints can only generate negative wedges, and therefore cannot account for the 51% of over-consumers, additional or alternative distortions are necessary to generate positive wedges. We identify two directions for theory to rationalize our findings. The first is to augment models featuring financial constraints to also include frictions that generate positive wedges, such as present bias (e.g., Lee and Maxted, 2023; Maxted, Laibson and Moll, 2024). The second is to include frictions that generate both positive and negative wedges, such as consumption adjustment costs and bounded rationality (e.g., Beraja and Zorzi, 2024; Ilut and Valchev, 2023). Both are sources of consumer inertia, which can create both positive and negative wedges by limiting the consumption response to shocks. In addition to these qualitative diagnostic implications, our quantitative results can also be used to calibrate structural models.

We verify that our two main findings are robust to alternative calibration choices regarding the preference parameters and the approximation points. A sensitivity analysis generally finds mild sensitivity and, at worst, that our baseline calibration is conservative regarding the typical size of wedges and degree of over-consumption. We also augment our baseline analysis to allow a plausible degree of preference heterogeneity, based on estimates in Aguiar et al. (2024). From this, we conclude preference heterogeneity likely counts for at most a small fraction of dispersion in the wedges. We also assess the potential impact of measurement error in consumption, wealth, income, and beliefs on our results in several analyses. Our findings remain similar when using alternative measurements.

Our last analyses provide further evidence on the interpretation and sources of the wedges. We begin by relating individuals' wedges to both their actual and hypothetical consumption behavior. We measure individual-level MPCs in response to stimulus checks received in 2021 and find that MPCs are positively correlated with wedges. This suggests that a force capable of generating positive wedges, such as present bias or consumer inertia, is likely a key reason for high MPCs out of transitory income shocks. We also compare wedges against answers to questions about hypothetical behavior, such as whether one would save more or save less if they expected higher inflation. Here we too find a positive association between wedges and hypothetically preferring to save less. This suggests that forces generating positive wedges are also important for consumers' responses to expected inflation.

We next examine the relationship between individuals' wedges and measures of their financial distress, housing tenure, and consumption commitments. For the first, we elicit measures of both perceived financial distress (such as anxiety about finances) and observable proxies (such as regularly having bank account balances below $500). We find that all of our proxies for financial distress are strongly positively correlated with wedges. This suggests that policy that aims to alleviate financial distress should be based on theories featuring forces that generate positive wedges, like present bias or inertia.

Separately comparing respondents with and without mortgages (as a proxy for homeownership), we find that people with mortgages on average have negative wedges. Positive wedges are 30% more common among people without mortgages. This pattern is consistent with financial constraints being the dominant friction for homeowners and present bias and/or inertia being most influential among households that do not own a home.

Regarding the potential role of consumption commitments, we construct a proxy based on the share of income spent on housing and childcare, two expenses that are typically large and difficult to adjust. We find that consumption wedges are positively correlated with consumption commitments, suggesting that they are another key ingredient to models of consumption choices. Taking stock, our results suggest that distortions beyond financial constraints—such as present bias and consumer inertia—are important drivers of consumer behavior.

Related Literature. Our paper contributes to several literatures. First, we build on the empirical macroeconomics literature studying the determinants of consumption. A central finding of this literature is large MPCs, especially among consumers with low liquid wealth (Johnson, Parker and Souleles, 2006; Baker, 2018; Fagereng, Holm and Natvik, 2021; Ganong and Noel, 2019). These cross-sectional patterns have served as important motivation for the inclusion of wealth heterogeneity and financial frictions in macro models (e.g., Kaplan and Violante, 2014; Koşar, Melcangi, Pilossoph and Wiczer, 2023). However, recent work has also found high MPCs among high-earning and wealthy households, which has motivated behavioral explanations, such as bounded rationality and present bias (e.g., Ilut and Valchev, 2023; Boutros, 2022; Lian, 2023; Maxted, Laibson and Moll, 2024).

Our findings can help refine the design of models by providing new data points the extent and direction of consumption distortions among low-liquidity households. The large size of the distortions we document highlights the importance of frictions in determining consumption for low-liquidity households. Additionally, the heterogeneity in (positive and negative) wedges and their correlation with MPCs support alternative models of frictions. Quantitatively, our results may also be useful calibration targets for models.

Methodologically, our analysis and findings also suggest that measuring micro-level wedges and using them to test alternative models of frictions could be a promising direction for future work. Our empirical approach is applicable to other settings, e.g., using only survey data. Notably, it does not require quasi-experimental variation, unlike the estimation of MPCs.

Second, we add to the empirical macroeconomics literature on consumer expectations. This literature has documented the importance of beliefs, including departures from FIRE, in explaining consumer behavior. D'Acunto et al. (2023) and Weber et al. (2022) provide recent reviews of this area. We complement recent papers that have linked consumption and beliefs data using, for example, survey measures (Coibion et al., 2023; D'Acunto et al., 2022), grocery shopping data through the Nielsen panel (Weber et al., 2023), German bank data (Hackethal et al., 2023), and credit card transactions (Kanz et al., 2021). Consumer beliefs appear to deviate from FIRE. For example, inflation expectations are excessively influenced by grocery prices (D'Acunto et al., 2021) and D'Acunto et al. (2024) finds evidence of extrapolative income expectations. Such findings motivate our use of subjective beliefs data to isolate the effects of frictions and behavioral preferences from distorted beliefs. Our consumption wedge analysis provides a novel demonstration and application of the value of consumer expectations.

Third, we contribute to the literature on wedge measurement by relaxing assumptions of FIRE and measuring wedges at the individual level. The business cycle accounting methodology of Chari et al. (2007) first popularized studying wedges between actual and frictionless values of aggregate variables. Subsequent work on wedges has focused on quantifying the importance of misallocation across firms and risk-sharing across households for growth and business cycles (e.g. Hsieh and Klenow, 2009; Baqaee and Farhi, 2020; Berger et al., 2023). Recently, Choukhmane and de Silva (2024) demonstrates an alternative approach to quantifying frictions that exploits quasi-experimental variation in constraints to separate the influence of beliefs and preferences from constraints, which they apply to study the determinants of stock market participation. Our approach to measuring wedges does not require quasi-experimental data and is able to separate the influence of beliefs from frictions and behavioral preferences.

Outline. We begin by introducing our frictionless benchmark and wedge measurement approach in Section 2. Section 3 describes our survey and linked transactions data. Section 4 presents our analysis of consumption wedges and Section 5 concludes.

2 Theory: Measuring Consumption Wedges

This section develops our approach to measuring consumption wedges. We present a frictionless benchmark model, which we use to characterize frictionless consumption. We then define consumption wedges as the difference between actual and frictionless consumption. These wedges can be calculated using data on consumption, income, wealth, and beliefs over future inflation, income growth, and interest rates. These variables are sufficient statistics for consumption wedges in a large class of models; we discuss the robustness of our formula for a variety of model extensions.

2.1 Frictionless Benchmark

Consumption-Savings Problem. A consumer lives for T periods. She chooses consumption C_t and savings A_{t+1} to maximize her expected utility subject to a budget constraint, solving:

$$V_t(Y_t, A_t, P_t, R_t) = \max_{\{A_{t+1}, C_t\}} u\left(\frac{C_t}{P_t}\right) + \beta \widetilde{E}_t \left[V_{t+1}(Y_{t+1}, A_{t+1}, P_{t+1}, R_{t+1})\right] \tag{1}$$

$$\text{s.t.} \quad C_t + A_{t+1} = Y_t + A_t R_t. \tag{2}$$

Every period, she receives income Y_t and her start-of-period wealth is $A_t R_t$, where A_t is her previous savings and R_t is the rate of return realized on her wealth. A negative value of A_t corresponds to borrowing. The price level in period t is P_t. Uppercase letters denote nominal variables and lowercase letters their real counterpart (i.e., real consumption is $c_t = \frac{C_t}{P_t}$). We assume the consumer has "standard preferences," which we take to mean time consistent, time separable, strictly increasing, strictly concave, and continuously differentiable.

The expectations operator $\widetilde{E}_t(\cdot)$ denotes the consumer's subjective expectation conditional on her information set at time t. We do not place restrictions on the contents of her information set. Her subjective expectations integrate over a conditional distribution of future possible values of income, wealth, prices, and interest rates. We do not require that her subjective conditional expectation follows Bayes' rule nor that it uses valid probability distributions. That is, she can have non-FIRE expectations.

There are three important features of this frictionless benchmark. First, it assumes that there are no frictions. That is, there are no borrowing constraints, transaction or adjustment costs, etc. Second, it assumes standard preferences. That is, it does not feature behavioral preferences like present bias or habit formation, which can result in "as if" constrained behavior. Third, the frictionless benchmark flexibly allows for deviations from FIRE. The first two features allow the consumption wedge to flexibly capture distortions due to either frictions or behavioral preferences. The third feature ensures that the consumption wedge does not conflate the influence of deviations from FIRE with constraints and behavioral preferences.

Optimal consumption $C_t^\star$ in the frictionless benchmark is characterized by the budget constraint in equation (2) and the Euler equation:

$$u'\left(\frac{C_t^\star}{P_t}\right) = \beta \widetilde{E}_t\left[u'\left(\frac{C_{t+1}}{P_{t+1}}\right)\frac{R_{t+1}}{\pi_{t+1}}\right] \tag{3}$$

where $\pi_{t+1} = \frac{P_{t+1}}{P_t}$ is the inflation rate.

Frictionless Consumption. We derive a closed-form, approximate expression for frictionless consumption, $C_t^\star$. We forward iterate the budget constraint and Euler equations, take a first order approximation, and combine them. This process yields the equation below (with derivation in Appendix B):

$$C_t^\star \approx \frac{A_t R_t + Y_t + Y_t \sum_{j=1}^{T}\left[\widetilde{E}_t G_{t,t+j}^{Y} \prod_{k=1}^{j}\left(\widetilde{E}_t R_{t+k}\right)^{-1}\right]}{1 + \sum_{j=1}^{T}\left\{\prod_{k=1}^{j}\left[\beta^{1/\gamma}\left(\frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}}\right)^{1/\gamma - 1}\right]\right\}}. \tag{4}$$

Equation (4) relates frictionless consumption $C_t^\star$ to three sets of objects. First are two preference parameters, the inverse intertemporal elasticity of substitution (IES) γ and the discount factor β. Second is start of period wealth $A_t R_t$ and income Y_t. Third are subjective expectations of gross nominal income growth $G_{t,t+j}^{Y}$ (from period t to $t+j$), annual inflation π_{t+j}, and gross annual nominal returns to wealth R_{t+j}. The numerator corresponds to (approximate) expected lifetime income. The denominator arises from using the approximate Euler equations to substitute out expected future consumption; it reflects the share of lifetime wealth the consumer wishes to consume in period t versus subsequent periods.

In general, frictionless consumption is increasing in initial wealth and income, as well as expected nominal income growth. The effect of a higher expected nominal interest rate is in general ambiguous, but will tend to be negative for $\gamma \geq 1$. Holding constant the expected nominal income and nominal interest rate, higher expected inflation affects consumption through two channels: it lowers real income (reducing consumption through an income effect) and it lowers real interest rates (increasing consumption through a substitution effect). For $\gamma \geq 1$, consumption is decreasing in expected inflation, as this leads the income effect to dominate the substitution effect.

2.2 Consumption Wedges

In the presence of distortions (frictions and behavioral preferences), actual consumption can deviate from frictionless consumption, creating a consumption wedge. Throughout, we normalize the consumption wedge by frictionless consumption, so that deviations are in percentage terms relative to frictionless consumption. For person i in time t, their consumption wedge is:

$$\eta_{it} = \frac{C_{it} - C^{\star}_{it}}{C^{\star}_{it}}. \tag{5}$$

Intuitively, the consumption wedge η_{it} measures how far "off their Euler equation" is their consumption. Because the frictionless benchmark excludes frictions and behavioral preferences, the consumption wedge quantifies the total impact of any and all such distortions on consumption. This includes constraints and adjustment costs, behavioral preferences, and bounded rationality (e.g., household consumption following a "simplified" policy function). Negative wedges correspond to "under-consumption" (i.e., consuming less than the frictionless benchmark) and positive wedges to "over-consumption."

Sufficient Statistics for the Consumption Wedge. Frictionless consumption is a known function of two preferences parameters (β, γ), initial wealth and income, and beliefs about income, inflation, and interests rates. With knowledge of these objects, along with actual consumption, it is possible to calculate a household's consumption wedge using Equations (4) and (5). Moreover, we discuss later that this wedge formula is robust to a variety of model extensions. As a result, these variables are sufficient statistics for consumption wedges in a broad class of models.

Example: Financial Constraints. To make the interpretation of wedges more concrete, we discuss several prominent frictions and behavioral preferences and how they relate to consumption wedges. We start with the primary friction considered by macroeconomics and household finance: financial constraints. These are most often modeled as a constant borrowing limit (e.g., Aiyagari, 1994), an endogenous borrowing limit (e.g., Bornstein and Indarte, 2023), or "soft" constraints arising from discrepancies in borrowing and saving rates (e.g., Kaplan et al., 2018). These frictions can introduce a wedge into the Euler equation, relative to the frictionless Euler Equation (3). For example, consider a constant borrowing limit such as $A_{t+1} \geq \overline{A}$. The Euler equation would be:

$$u'\left(\frac{C_t}{P_t}\right) = \beta \widetilde{E}_t \left[u'\left(\frac{C_{t+1}}{P_{t+1}}\right) \frac{R_{t+1}}{\pi_{t+1}} \right] + \mu_t$$

where $\mu_t \geq 0$ is the Lagrange multiplier. The Lagrange multiplier μ_t is positive if and only if the constraint is binding. All else equal, a binding constraint reduces consumption C_t. An important feature of financial constraints is that they only generate negative consumption wedges. Therefore, a testable implication of financial constraints is the sign of the consumption wedges. The presence of positive wedges would indicate that financial constraints are insufficient to rationalize empirical consumption choices.

Example: Present Bias. Present bias is a behavioral preference that features time inconsistency. Consider for example, beta-delta discounting, where agents discount future utility by an additional factor $\overline{\beta} < 1$ relative to the standard exponential discounting model (where δ is the exponential discount factor, corresponding to β in our notation above). Under these preferences, the expectation term in the Euler equation is scaled down by the degree of present bias ($\overline{\beta}$):

$$u'\left(\frac{C_t}{P_t}\right) = \overline{\beta}\delta\widetilde{E}_t\left[u'\left(\frac{C_{t+1}}{P_{t+1}}\right)\frac{R_{t+1}}{\pi_{t+1}}\right]$$

As a result, these preferences cause consumption to be higher relative to a "debiased" ($\overline{\beta} = 1$) consumer (Maxted, 2022), all else equal. Hence, present bias creates positive wedges. Similar to financial constraints, we can use the sign of empirical consumption wedges to test whether present bias is sufficient to rationalize empirical consumption choices.

Example: Inertia. Another class of distortions introduces inertia into consumption choices. One example is consumption commitments, where inertia is generated by consumption adjustment costs (e.g., Chetty and Szeidl, 2007; Beraja and Zorzi, 2024) or Calvo-style adjustment shocks (e.g., Auclert, Rognlie and Straub, 2020; Bornstein, 2021). Another is habit formation, which is a preference-based source of inertia where the utility of current consumption depends on past consumption (e.g., Fuhrer, 2000; Christiano et al., 2005; Smets and Wouters, 2007). This history dependence violates the time separability assumption of our benchmark and will therefore also be captured by our consumption wedge formula. Bounded rationality can similarly create inertia when costly cognition limits or delays consumption adjustments. For example, in Ilut and Valchev (2023), cognition costs limit households' updating of consumption decision rules, leading to inertial behavior. This class of frictions can produce either positive or negative consumption wedges. To see this, consider a consumer facing a convex utility cost of adjusting their consumption: $\phi(C_t - C_{t-1})$. In such a case, the Euler equation would have additional terms reflecting this cost:

$$u'\left(\frac{C_t}{P_t}\right) - \phi'(C_t - C_{t-1}) = \beta\widetilde{E}_t\left\{\left[u'\left(\frac{C_{t+1}}{P_{t+1}}\right) - \phi'(C_{t+1} - C_t)\right]\frac{R_{t+1}}{\pi_{t+1}}\right\}.$$

Under these inertial preferences, inertia can limit the downward adjustment of consumption following negative wealth shocks, as adjustments incur a penalty, resulting in positive wedges (overconsumption). Similarly, positive shocks can lead to negative wedges. Empirical findings of both positive and negative wedges could be rationalized by this class of distortions.

Empirical evidence on consumption wedges can help guide the choice and modeling of frictions. Qualitatively, the presence of both positive and negative wedges would indicate that neither financial constraints nor present bias alone are sufficient to explain empirical consumption choices. Quantitatively, estimates of wedges, their distribution, correlations with observables, or reactions to shocks could also be used to calibrate quantitative models and thus also discipline the parameters governing distortions.

2.3 Model Extensions

Our frictionless benchmark intentionally abstracts away from many real-world features for two reasons. First, by positing a benchmark without frictions or behavioral preferences, the benchmark is a "special case" in a large class of models. That is, the benchmark corresponds to versions of richer models where frictions and behavioral preferences are turned "off." For example, in a model with borrowing constraints, our benchmark corresponds to infinite borrowing constraints. In a model with beta-delta discounting, it corresponds to zero present bias (i.e., $\beta = 1$ in the notation of Maxted, 2022). Abstracting away from frictions and behavioral preferences enables the wedges to measure the effect of all such distortions on consumption.

Second, to simplify the exposition we do not explicitly model other choices households make, such as labor supply. This is without loss of generality because our characterization of frictionless consumption only requires that the budget constraint and Euler equations are necessary conditions for optimality. They need not be sufficient. Below, we discuss a variety of model extensions and their implications for interpreting and measuring consumption wedges.

Additional Household Choices. The consumption wedge formula remains unchanged and its interpretation similar when allowing additional household choice variables, such as labor supply. Adding choice variables results in additional optimality conditions. But as long as an Euler equation and budget constraint continue to be necessary conditions for optimality, the consumption wedge formula is unaltered. When these other choices are subject to frictions (e.g., labor income taxes), if these frictions are reflected in the budget constraint (income is measured on an after-tax basis), the distortionary effects of these frictions are not reflected in the consumption wedges.[5]

[5] Continuing with the labor income tax example, if taxes are netted out of the budget constraint, their income effect on consumption is not reflected in the consumption wedge. Suppose the taxes distort other decisions, like labor supply, affecting affect resources available in the budget constraint. In this case, the consumption wedges still describe the effect of distortions to the consumption-savings decision, but this effect is "local" in the sense of being conditional on expected after-tax income (which may be distorted by taxes).

Additional Assets. We can also enrich the frictionless benchmark to feature a portfolio choice problem where the household chooses a mix of assets and liabilities, including housing. In such a model, there is an Euler equation for each asset. Taking a portfolio-weighted sum of the Euler equations across each asset yields another Euler equation in terms of the portfolio's return. It is this Euler equation, featuring the (possibly leveraged) portfolio return, that one would use to characterize frictionless consumption. In our application we consider two securities: savings and debt. For each household, we measure their wedge using their expected portfolio return, which depends on their leverage and beliefs about the return to savings ($\widetilde{E}_{it}R^S_{it}$) and cost of debt ($\widetilde{E}_{it}R^D_{It}$) as follows:

$$\widetilde{E}_{it}R_{it} = \frac{S_{it}}{S_{it} - D_{it}}\widetilde{E}_{it}R^S_{it} - \frac{D_{it}}{S_{it} - D_{it}}\widetilde{E}_{it}R^D_{it} \tag{6}$$

where S_{it} is their total assets and D_{it}, their total liabilities (making the ratios above correspond to portfolio weights). Ideally, one would measure the portfolio return using beliefs data on all individual assets and liabilities facing households. This would be most important when measuring wedges for households with larger and more complex portfolios. However, because the households in our empirical setting have little wealth, measurement error from focusing on two securities (savings and debt) is likely milder. A majority of respondents in our sample do not have a mortgage (and thus are unlikely to be homeowners); we also study these households separately as measurement error is also likely lower for non-homeowners, as their portfolio returns would not depend on expected house price appreciation.

Durable Goods. The wedge formula is not altered by the presence of durable goods. The logic is similar to the other endogenous choices discussed above. However, durable goods do present measurement challenges for applying the consumption wedge formula. Consumption of durable goods is difficult to measure because they yield a flow of consumption services over time after an initial purchase. To overcome this, Appendix B.2 formally introduces durable goods to our framework. The key assumption we make is that notional (i.e., composite) consumption is a Cobb Douglas aggregate of non-durable and durable consumption flows. This assumption allows us to impute the APC for total consumption from non-durable consumption and an estimate of the non-durable share of expenditures.

Heterogeneity. In a model with a single representative household, the aggregate or average wedge would be the appropriate object of interest. For models with multiple households, a distribution of consumption wedges can be calculated. If one finds empirically that there is significant heterogeneity in wedges, this would indicate that frictions and/or behavioral preferences are important determinants of cross-sectional heterogeneity in consumption. For the class of models where heterogeneity in consumption behavior affects aggregate outcomes (e.g., Kaplan and Violante, 2014), this would imply that correctly modeling frictions and/or behavioral preferences is important for predicting aggregate outcomes (in addition to the distribution of welfare).

2.4 Why Wedges?

Consumption-savings choices are the linchpin for wide-ranging areas of economics, providing the micro foundations that anchor fiscal- and monetary-policy multipliers, optimal tax-and-transfer design, and asset price dynamics. The micro-level consumption wedges that we introduce here can advance our ability to model consumption-savings behavior in two ways. First, by estimating the distribution of wedges and their relationship to other variables of interest, we can improve qualitative model selection and help distinguish between competing frictions and behavioral preferences to identify those which best reconcile behavior. Second, consumption wedges can serve as a new calibration target for quantitative models, without requiring quasi-random variation to estimate, unlike MPCs.

Consumption wedges are well-suited for both these objectives. Their formula is the same within a broad class of models, they do not require the assumption of FIRE to measure nor calibrate a model, they separate the influence of beliefs from frictions and behavioral preferences, and they facilitate the a rich characterization of micro-level heterogeneity. Prior wedge analyses in the vein of Chari et al. (2007) and Berger et al. (2023) assume FIRE because it makes it possible to measure wedges without beliefs data. Under FIRE, one can measure expectations by averaging over realizations—either across time using the ergodic distribution of an estimated stochastic process or across agents with similar characteristics. If beliefs do deviate from FIRE, the effect of these deviations on consumption would be conflated with the impact of other distortions. By eliciting beliefs, we are able to separate the influence of deviations from FIRE from frictions and behavioral preferences. Moreover, because we do not need to average across individuals to calculate wedges, we can measure individual-level wedges. These "micro" wedges are useful because aggregate wedges, even if they are near zero, may mask significant heterogeneity, which can be an important determinant of macro transmission (Kaplan and Violante, 2014).

Euler equation residuals have been used in prior work to estimate time and risk preferences, under the assumption of no distortions. An early literature used consumption data and GMM to estimate homogeneous preference parameters with any remaining residuals interpreted as measurement error (e.g., Hall, 1978; Hansen and Singleton, 1982; Attanasio and Weber, 1995). These papers generally assume rational expectations, with Crump et al. (2022) being a rare exception. Variants interested in measuring preference heterogeneity generally assume that consumers face neither frictions nor behavioral preferences, and ascribe all deviations from the Euler equation to preference heterogeneity. Our interpretation of the consumption wedges we estimate will emphasize the influence of these distortions, though we note that the wedges would also reflect preference heterogeneity when measured under our assumptions of homogeneous preferences. In support of this focus, we later show robustness tests allowing plausible preference heterogeneity (as estimated in Aguiar et al., 2024) and conclude that preference heterogeneity likely plays a much smaller role than frictions and behavioral preferences in generating consumption wedges. A useful direction for future research would be to solicit preference parameters along with beliefs in a survey, making it possible to calculate wedges using individual-specific preferences.

Consumption wedges have some advantages relative to typical objects used to motivate model selection like MPCs and proxies for model features (e.g., financial constraints). Estimating MPCs requires quasi-random shocks to income. Moreover, consumers may respond differently to these windfalls (e.g., lottery winnings) than typical shocks to income, or the income shocks may occur in particularly fraught economic environments (e.g., stimulus checks). Evidence suggests that MPCs are state dependent and depend on the size of the income shock (Fagereng et al., 2021), which can complicate mapping empirical estimates to model analogs. Emerging evidence also suggests that part of the empirical consumption response to shocks may not correspond to a "pure" MPC, as shocks may indirectly alter consumption by changing expectations of future income (Yin, 2025). While wedges are also specific to the context in which they are measured, they do not require quasi-random variation to calculate and can be measured using observational data in any environment.

Economists often use proxies like credit card utilization or low liquid wealth to identify financially constrained consumers. While such proxies may serve as useful ordinal indicators—ranking households by the likelihood or severity of distortions—in the absence of a fully specified model, they offer no cardinal measure of how distorted consumption actually is. Consumption wedges overcome this limitation by directly measuring the impact of distortions on consumption. Moreover, while proxies like low liquidity may be indicative of financial constraints, low liquidity can also arise from other distortions. For example, present bias or inertia could also generate low liquidity through a history of over-consuming and under-saving. Consumption wedges improve our ability to diagnose both the nature and importance or distortions, helping to better distinguish between competing models of distortions.

In Section 4.4, we explore the relationship between the consumption wedges and MPCs, proxies for financial distress, and proxies for various distortions. The patterns we document challenge the conventional view that financial constraints are the main cause of high MPCs, or that financially distressed households are most often in a state of under-consumption.

Finally, both consumption wedges and MPCs can serve as calibration targets for quantitative models. It is difficult to empirically estimate a distribution of MPCs (and how that distribution varies with the state of the economy).[6] As a result, models are often disciplined by a single estimate of an MPC (or estimates for several groups). While our analysis uses administrative consumption data to minimize measurement error, in principle one could use a survey to solicit all of the necessary inputs to measure consumption wedges. This flexibility gives consumption wedges a practical advantage as calibration targets: they can be constructed for a wide range of populations and time periods, even in settings where exogenous income shocks are unavailable or hard to isolate.

3 Data and Survey Design

3.1 Data Sources

EarnIn Administrative Data. We receive anonymized data measuring individuals' spending and income based on bank transactions recorded by EarnIn, a US-based financial technology company that allows individuals to access a portion of their earnings before their official payday. This "earned wage access" (EWA) product is available to individuals with regular pay schedules, a fixed work location or electronic timekeeping system, and a connected bank account. EarnIn maintains an administrative database that includes users' account information, bank account transactions and balances, earnings, and EWA cashout activity. Bank account transactions are categorized by Plaid, a financial services company that facilitates connections between users' bank accounts and the EarnIn app. For an overview of the structure of the EarnIn data, see Appendix C. The EarnIn database covers over eight million US residents as of November 2024.

Our baseline analysis covers the 12-month period before each survey wave (e.g., October 2021 to September 2022 for wave 1). Our primary object of interest is the average propensity to consume (APC) out of income, defined as annual spending divided by annual income. Appendix C details our methodology for categorizing outflows and inflows in bank transactions. We define our measure of spending as outflow transactions that can be categorized as non-durable spending.

[6] Recently, (Lewis, Melcangi and Pilossoph, 2024) estimate a distribution of MPCs by assuming that household-level error terms (in regressions of consumption on income shocks) are normally-distributed. Even with these advances, estimating the full state dependence of MPCs (on the macroeconomic state, policy stance, shock size, etc.) remains challenging.

We focus on non-durable spending because it corresponds more closely to consumption, whereas the relationship between spending and consumption of durables depends on their rate of depreciation and the flow of services rendered. We measure income as the sum of post-tax earnings and unemployment insurance (UI) benefits. We classify inflow transactions as either earnings (observed post-tax), UI benefits, or "other" using a combination of the observed earnings data with the Plaid categorization, memo line, and periodicity of the transaction.

Survey Data. We link the EarnIn database with survey responses for nearly 15,000 users covering demographics, household finances, and subjective economic expectations. Among prior studies, data containing both subjective economic expectations and comprehensive transactions are rare (D'Acunto et al. (2021) link economic expectations to grocery spending; Kanz et al. (2021) with credit card spending.) Our dataset allows us to link expectations with earnings, spending, and savings data that can paint a near-comprehensive picture of a consumer's economic activity at a high frequency. To our knowledge, we are the first to gather this data for US consumers—in contemporaneous work, Hackethal et al. (2023) and D'Acunto et al. (2024) link similar data for users of German and Chinese banks, respectively.

EarnIn fielded the survey in three waves between 2022 and 2024. Wave 2 was a follow-up survey sent to respondents from wave 1. In each wave, qualifying users were invited via EarnIn's standard email marketing channels to complete a short survey about their current economic well-being and future outlook. Survey windows spanned from September 29 to October 2, 2022 (wave 1); July 12 to July 19, 2024 (wave 2); and November 22 to December 4, 2024 (wave 3). Surveys took five to ten minutes (wave 1) or ten to fifteen minutes (waves 2 and 3) to complete. As an incentive, respondents received a $5 (waves 1 and 3) or $10 (wave 2) Amazon gift card upon completion.

To construct the sampling frame for each wave, we imposed data quality requirements on the transactions data to ensure the users' linked accounts captured their economic activity. For waves 1 and 3, we restricted to users for whom we observe earnings, regular spending, and balances in the 12 months leading up to the survey, and who had not yet reached EarnIn's weekly email marketing limit. For the wave 2 follow-up survey, we invited only wave 1 respondents who met additional data quality restrictions and had not yet reached the email marketing limit. Across all three surveys, EarnIn sent approximately 475,000 survey invitations and received approximately 15,866 responses, yielding an aggregate response rate of 3.4%. The median survey completion time among respondents was 7.5 minutes. See Appendix C for additional detail on sampling construction and response rates by survey wave.

We elicited expectations for inflation, income growth, and interest rates in each survey wave.

For inflation, respondents were asked to estimate inflation over the past 12 months and to forecast inflation over two future horizons: 0-12 months (short-run) and 24-36 months (medium-run). The phrasing of these questions was based on similar questions from the University of Michigan Survey of Consumers (MSC) and the Federal Reserve Bank of New York Survey of Consumer Expectations (SCE). We also asked respondents to forecast their personal income growth over the next 12 months, the percentage yield they would expect on additional savings over the next 12 months, and the percentage rate they would pay on new borrowing over the same period. In addition to these expectations questions, we asked respondents how a hypothetical increase in inflation would affect their saving and why.

We also elicited several measures of financial distress. We asked respondents whether they perceive their debt as manageable, whether they have been denied for credit, and whether they have anxiety relating to their finances, among other questions. We also asked about usage of alternative financial products such as payday loans, pawn shops, and cash checking services. To measure financial literacy, we asked the two of the "Big 5" financial literacy questions about interest rates and inflation (Lusardi and Mitchell, 2014).

Each survey wave also included questions on demographics and household finances. The demographic questions covered age, gender, race, household structure, education, and political affiliation. To capture household finances, we asked respondents to report their total household income, savings, and debt in binned dollar ranges, and whether they held outstanding debt in the form of a mortgages, auto loans, student loans, medical bills, or credit card balances.

In waves 2 and 3, we added several survey questions to expand our wedge measurement and analysis. Beginning in wave 2, we elicited respondents' expected spending growth over the next 12 months, enabling our measurement of the static wedge. We also measured respondents' owner versus renter status; their monthly rent, mortgage, and childcare payments; and their risk and time preferences. In wave 3, we elicited respondents' hypothetical marginal propensity to spend, repay debt, and save out of a $1,000 one-time income shock.

Sample Restrictions for Analysis. We impose a series of sample restrictions for our analysis, detailed in Appendix C. We exclude responses flagged for inattention or low effort by requiring a minimum survey duration of 3.5 minutes, internally consistent responses, and economic expectations within reasonable bounds.[7] We also drop users with insufficient transactions data coverage in the 12 months surrounding the survey, and we trim outliers for key financial variables (nondurables spending, income, APC, wealth-to-income, and expected levered return). After all

[7] We retain respondents with inflation and income growth expectations between the 3rd and 97th percentiles and interest rate expectations between the 1st and 97th percentiles.

restrictions, our analysis sample includes 6,243 survey responses from 5,961 unique users.

Imputing Wealth Our survey solicited binned measures of liquid assets and total debt, but not illiquid assets. To obtain a more complete and precise measure of net worth AR/Y, we leverage our detailed economic, financial, and demographic data and train a machine learning model (XG-Boost) to predict illiquid assets, as well as a numerical value for liquid assets and debt constrained to fall within the user's self-reported bin. We estimate the model using data from the Survey of Consumer Finances, following the procedure detailed in Appendix D.1.

3.2 Summary Statistics

Table 1 presents summary statistics for our analysis sample. Compared to the US population, our sample skews younger (median age of 36), female (69% of respondents), and non-white (45%). Respondents exhibit a high degree of financial distress: 64% report having less than $500 in savings, 72% report having an unmanageable amount of debt, and 52% report having high anxiety related to their finances. Forty-three percent of respondents have a college degree, and 45% correctly answered both financial literacy questions.

Relative to the US population, our sample is concentrated among individuals with low liquidity (Appendix Figure E.1), but the distribution of labor income in our sample is broadly representative of the full US population (Appendix Figure E.2). The median respondent has $39,639 annual post-tax income, $16,873 in total debt, and $19,679 in total assets – but only $250 in liquid assets. Only 18% of respondents have a mortgage. With respect to labor income, our sample has good coverage from the 10th to the 90th percentile of the distribution of US labor income distribution, with slight overrepresentation of those between the 25th and 75th percentiles.

The median one-year-ahead inflation expectation in our sample is 5%. Respondents expect inflation to come down slightly, with a median three-year inflation expectation of 4%. The median estimate of realized inflation over the prior year is 7% – higher than standard inflation measures, but potentially reflective of the consumption baskets faced by our middle-income, low-liquidity sample. The median respondent forecasts nominal income growth of 3% over the next year, on average, implying an expected real income decline of -2%. Reported interest rate expectations on marginal savings and borrowing are broadly reasonable, with medians of 2% and 15%, respectively.

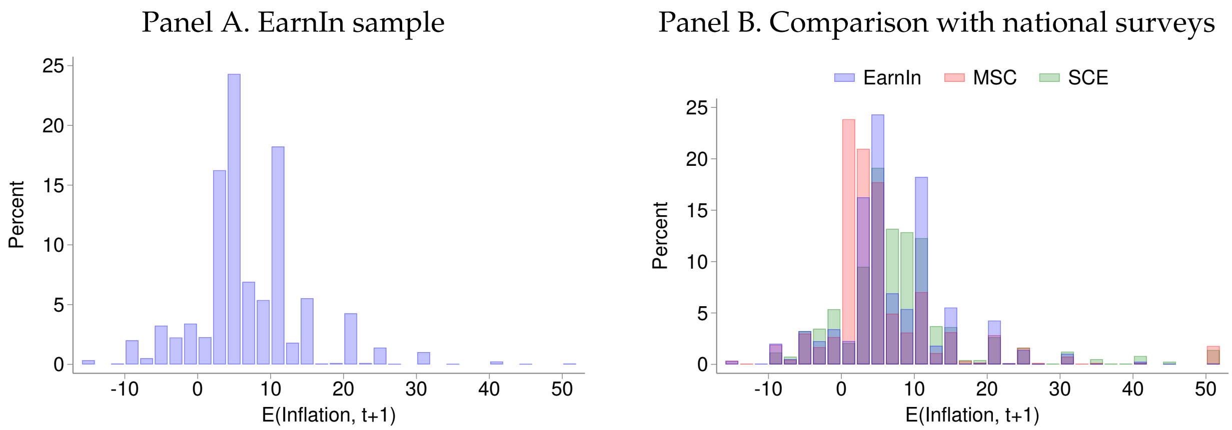
Inflation expectations in our sample are broadly consistent with those of nationally representative samples, particularly the SCE. Figure 1 presents the distribution of inflation expectations in our survey relative to MSC and SCE respondents from the same time period. Our survey sample

Table 1. Summary Statistics

	Mean (1)	SD (2)	P25 (3)	P50 (4)	P75 (5)	N (6)
Panel A: Demographics						
Female (%)	69	.	.	.	.	5,272
White (%)	55	.	.	.	.	5,181
Age	37	9	31	36	43	5,254
Has children (%)	51	.	.	.	.	5,272
Spouse or partner (%)	54	.	.	.	.	5,272
College (%)	43	.	.	.	.	5,272
Panel B: Household finances						
Liquid assets ($)	1,466	3,489	236	250	750	5,272
Total assets ($)	42,949	62,398	8,039	19,679	42,125	5,272
Total debt ($)	43,344	55,939	7,503	16,873	39,960	5,272
Has mortgage (%)	18	.	.	.	.	5,272
Liquid net worth ($)	-41,878	55,565	-39,287	-16,159	-6,968	5,272
Total net worth ($)	-395	40,144	-13,981	-224	12,947	5,272
Nondurables spending ($)	29,944	13,570	19,954	26,915	37,292	5,272
Income ($)	43,696	19,337	30,058	39,639	53,173	5,272
Liquid net worth to income (%)	-94	124	-122	-47	-19	5,272
Total net worth to income (%)	-2	87	-39	-1	33	5,272
Nondurables C/Y (%)	72	25	54	68	85	5,272
Panel C: Economic expectations						
Perceived inflation (%)	9	9	5	7	10	3,246
E(Inflation, 1Y) (%)	7	7	3	5	10	5,272
E(Inflation, 3Y) (%)	4	8	-2	4	8	5,272
E(Income growth) (%)	5	9	2	3	5	5,272
E(Rate on savings) (%)	3	3	1	2	4	5,272
E(Rate on borrowing) (%)	15	10	7	15	24	5,272
E(Levered return) (%)	16	10	7	15	25	5,272
E(Spending growth) (%)	6	66	-2	5	10	2,355
Panel D: Financial constraints						
Liquid assets below $500 (%)	64	.	.	.	.	5,272
High financial anxiety (%)	52	.	.	.	.	5,271
Debt unmanageable (%)	72	.	.	.	.	5,270
Difficulty borrowing (%)	48	.	.	.	.	5,271
High financial literacy (%)	45	.	.	.	.	5,272
EarnIn EWA usage ($)	5,410	3,979	2,612	4,593	7,254	5,272
EarnIn EWA usage / income (%)	14	12	6	11	19	5,272
Panel E: Consumption commitments						
Has mortgage (%)	18	.	.	.	.	5,272
Consumption commitments ($)	1,695	3,497	1,000	1,500	2,058	2,280
Commitments / income (%)	55	88	30	45	67	2,280
Panel F: Response to an income shock						
Observed nondurables MPC (%)	28	34	3	25	53	2,474
Hypothetical MPC (%)	21	24	0	20	30	2,008
Hypothetical MPRD (%)	68	36	50	75	100	2,016
Hypothetical MPS (%)	11	36	0	0	0	2,008

Notes: The table presents summary statistics for our analysis sample after trimming wedges at the 1st and 95th percentiles, which consists of 5,034 EarnIn users. Columns (1) through (5) show the distribution of each variable, and column (6) shows the number of survey responses with non-missing data. See Appendix C.4 for variable definitions.

Figure 1. Distribution of Inflation Expectations



Notes: The figures show the distribution of one-year ahead inflation expectations in the EarnIn sample (left) relative to the distributions in the Michigan Survey of Consumers (MSC) and NY Federal Reserve Survey of Consumer Expectations (SCE) (right). To match the timing of the EarnIn surveys, we use MSC and SCE data from September 2022, July 2024, and November 2024 (the SCE data is unavailable in November 2024) and reweight the data based on the share of the EarnIn sample in each survey wave.

is also slightly more likely to report round numbers divisible by five. Appendix E.3 presents our respondents' self-reported expectations for inflation, nominal income growth, and interest rates against their realized values. In general, we find that the median forecast error is small.[8]

4 Empirical Analysis of Consumption Wedges

This section measures and analyzes consumption wedges for our survey population. We begin by describing the calibration of the parameters in the wedge formula. We then present the distribution of observed consumption wedges, from which we glean two of our main insights. First, the typical wedge is large—in absolute value, the median wedge is 40% of frictionless consumption. This indicates that frictions and/or behavioral preferences are significant determinants of consumption for households with low-liquid wealth, and hence distortions are important for modeling their consumption-saving decisions. Second, we find that 51% of the sample have positive wedges (over-consumers), which cannot arise from financial constraints. The mix of positive and negative wedges can be rationalized either by a combination of financial constraints and present bias, or by consumer inertia. We then show that our findings of large wedges and a large over-

[8]The analysis of forecast errors provides qualitative evidence that the survey instrument captures reasonable expectations, but cannot precisely identify biases in individual respondents' expectations. We cannot observe individual-level realizations of inflation and interest rates because we do not observe each respondent's distinct consumption basket and asset mix. We therefore cannot isolate forecast bias from individual deviations, aggregate inflation rates, or interest rates.

consumer share are robust to model calibration choices, preference heterogeneity and measurement error. Lastly, we correlate wedges with observables to test alternative theories about the sources of the consumption distortions.

4.1 Calibration

To measure consumption wedges for our survey sample, we begin by calculating each respondent's approximate frictionless consumption via Equation (4), which we reproduce below:

$$C_t^\star \approx \frac{A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \prod_{k=1}^{j} \left(\frac{\widetilde{E}_t G_{t+k}^Y}{\widetilde{E}_t R_{t+k}} \right)}{1 + \sum_{j=1}^{T} \left\{ \prod_{k=1}^{j} \left[\beta^{1/\gamma} \left(\frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{1/\gamma - 1} \right] \right\}}.$$

Throughout, we assume that households face an infinite horizon ($T \to \infty$). We calculate net worth based on our survey data, and income based on transactions data. We assume two preferences parameters (β, γ). Lastly, we make assumptions to characterize the term structure of beliefs. We next detail our approach.

Calibrating Preference Parameters. Our baseline calibration uses standard values for the annual discount factor ($\beta = 0.92$) and the inverse IES ($\gamma = 2$).[9] In Section 4.3, we perform sensitivity analyses to demonstrate the robustness of our main results to alternative choices for these preference parameters as well as robustness to preference heterogeneity.

Expected Returns. For the gross interest rate $\widetilde{E}_{i,t} \ln R_{i,t+1}$, ideally one would measure the expected gross portfolio return. This is because the budget constraint depends on the total return across all assets and debts. But measuring this requires knowing expected returns for all assets and debts, as well as their portfolio shares. To minimize survey attrition, our survey questions focused on two expected interest rates: the return to saving and the cost of debt. The phrasing in our survey's savings interest rate question likely solicits beliefs about *liquid* assets. To overcome a lack of data on expected returns to illiquid assets, we assume that the expected return on each respondent's illiquid assets equals the expected return on their portfolio of liquid assets and debt. Under this assumption, we calculate the expected gross portfolio return as the weighted average of expected gross interest rates on savings and debt, where the weights are obtained by dividing both liquid wealth and debt by their sum (respectively).

[9] Discount factors close to 0.90 are common in models featuring unsecured consumer borrowing, such as Bornstein and Indarte (2023).

Term Structure of Beliefs. Frictionless consumption depends not only on one-year-ahead beliefs but also on the entire term structure of beliefs. Our survey solicits one-year-ahead beliefs over nominal income growth, interest rates, and inflation, as well as a three-year-ahead belief for inflation. We impute the remaining term structure. For inflation expectations, we use data on one to thirty-year-ahead expected inflation (measured via inflation swaps). Our approach is motivated by the observation that the ratio of one- to three-year-ahead beliefs is similar to that of the swaps-implied beliefs (measured in the same month of each survey wave).[10] For interest rates, we assume the expected gross rate is constant (i.e., a flat term structure). Lastly, the term structure of income likely reflects lifecycle considerations. To impute this, we use data from the Survey of Consumer Expectations (SCE), which solicits one-year-ahead income expectations for a broad population of US residents. Using data on all available years, we find that one-year-ahead expected nominal income growth appears to exponentially decay with age. We estimate this rate of decay in the SCE and use it to extrapolate income expectations for our sample. We detail our imputation procedures in Appendix D. In Appendix Figure F.6, we show the distribution of wedges under an alternative assumption of constant beliefs. Allowing one-year beliefs to persist indefinitely results in more outliers and higher absolute value of wedges, but the shape of the distribution is otherwise similar to those resulting from our baseline extrapolated expectations.

Income and Consumption Measurement Assumptions. To calculate the wedge, we subtract frictionless consumption from actual consumption, and divide this quantity by frictionless consumption. To measure actual consumption, we begin by calculating non-durable consumption using data from the 12 months prior to and including the survey month for each wave (i.e., October 2021 to September 2022 for Wave 1).[11] To obtain total or ”notional” consumption (i.e., the argument of the utility function), we divide each respondent's non-durable consumption by the expenditure share of non-durable goods (79.37%). Under the assumption that notional consumption is a Cobb-Douglas aggregate of durable and non-durable good consumption flows, this calculation yields the notional consumption (for a proof, see Appendix B.2). We obtain the non-durable expenditure share from Beraja and Zorzi (2024), which calculates it using Consumer Expenditure Survey data.

[10] The median ratio of one- to three-year-ahead inflation expectations in the EarnIn sample is 1.0 for each survey wave, comparable to the ratio for swaps-implied beliefs (1.03 in October 2022, 1.04 in July 2024, and 1.16 in November 2024).

[11] Conceptually, we want to measure time t consumption wedges using time t consumption and time t beliefs about $t+k$ variables. We verify that we obtain similar results when using all 12 months as separate measures of consumption, or when aggregating consumption over fewer pre-survey months (e.g., the month of the survey only). See Appendix Figure F.5.

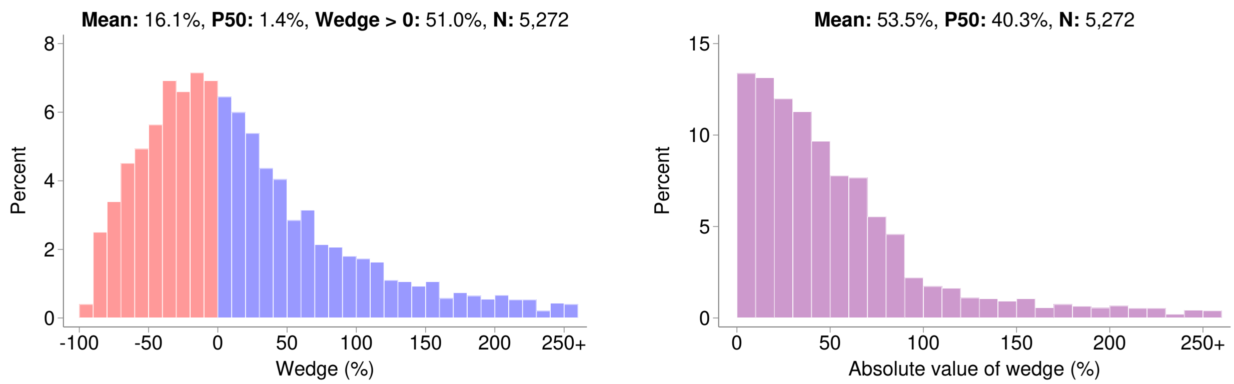
4.2 Results: Empirical Consumption Wedges

Calculating consumption wedges for each respondent, we find large wedges and significant heterogeneity. Figure 2 displays histograms of measured wedges. Our first main finding is that many consumers have significantly distorted consumption. The average wedge is approximately 16% (Panel A), indicating that the average respondent has consumption distorted upwards 16% relative to their counterfactual frictionless consumption. Taking the absolute value of wedges, we find that the median distortion is 40% (Panel B). Further examining the absolute value wedges, we see that the modal respondent has a distortion less than 30%. It is notable that not all consumers have large wedges, especially given the prevalence of low-liquidity households in our sample. Approximately 13% of the sample has consumption within 10% of frictionless consumption. These households either face minimal distortions or offsetting distortions—for example, a consumer may be present biased but financial constraints limit their ability to over-consume.

Figure 2. Distribution of Dynamic Consumption Wedges

Panel A. Raw wedges

Panel B. Absolute value of wedges



Notes: The figures show the distribution of dynamic consumption wedges (left) and their absolute values (right). Wedges are defined as the percent difference between the observed APC and frictionless APC, and they are trimmed at the 1st and 95th percentiles.

Overall, the histograms reveal that many consumers in our sample face large distortions to their consumption. The large size of these distortions indicates that frictions and/or behavioral preferences are an important determinant of the consumption choices of low-liquidity households. Therefore, these distortions are important to include in models of consumer behavior featuring such households.

Our findings also highlight the value of studying micro-level wedges, as opposed to macro-level (aggregate or average) wedges. The average wedge is less than half the magnitude of the median absolute value wedge (16% versus 40%). The median (non-absolute value) wedge is even smaller: 1.4%. Without observing the distribution, one could significantly underestimate the importance of distortions in the consumption decisions of low-liquidity consumers. In many modern macroeconomic models, heterogeneity in consumption behavior matters in the sense that it influences aggregate consumption (e.g., Kaplan and Violante, 2014; Maxted et al., 2024). For the class of models where such heterogeneity affects the aggregate economy, knowledge of the *distribution* of consumption wedges may be especially helpful for disciplining the choice and quantitative modeling of frictions and behavioral preferences.

Our second main finding is that many households have positive wedges (over-consume). Specifically, 51% of households are over-consuming relative to their frictionless consumption. This finding challenges the dominant modeling paradigm in household finance and macroeconomics: that financial constraints are the key friction shaping the consumption choices of low-liquidity households. As discussed in Section 2, financial constraints only generate negative wedges. While financial constraints could explain the 49% of consumers with negative wedges, such constraints cannot be the dominant friction for the other 51%. Financial constraints are therefore unable to account for the behavior of a large fraction of consumers in our sample. By similar logic, the presence of negative wedges also rejects present bias as the sole friction/behavioral preference facing the low-liquidity households in our sample. Neither financial constraints nor present bias alone can rationalize the mix of positive and negative wedges. A different model is necessary; we identify two promising alternatives. A first solution is including both present bias and financial constraints. The second alternative is the set of distortions that create inertia in consumption. These include consumption adjustment costs, habit formation, and forms of bounded rationality that results in sticky behavior (e.g., Ilut and Valchev, 2023).

Our sample has a high demand for liquidity and one might therefore expect the wedges to be especially large, and especially negative if financial constraints are the dominant friction distorting their consumption. In assessing the magnitude and distribution of wedges, it is important to keep these features of our sample in mind. This makes the significant share of over-consumers we estimate particularly surprising. EarnIn EWA usage in terms of dollars is slightly negative; as a share of income there is a small but positive correlation of usage with the wedges (see Appendix Figure A.4). These small economic magnitudes suggest that there is unlikely significant selection into our sample related to having positive or negative wedges.

A valuable endeavor for future research would be to compare the ability of the two alternative classes of models described here to match empirical patterns in consumption wedges using quantitative structural models. For example, would a model with empirically realistic negative skewness of income shocks (Guvenen et al., 2021) struggle to generate a mix of mostly negative wedges?

We next assess the robustness of the results to calibration choices and measurement error. Following this, we then correlate wedges with other observables to provide additional insights into the nature of the underlying distortions. This yields additional guidance for the choice of distortions. We also provide additional moments that are better-suited targets for calibrating quantitative models because they are less likely to be affected by our analysis sample not being a representative cross-section of the US.

4.3 Robustness

We examine the robustness of our two main findings: (1) median absolute value wedge of 40% and (2) 51% share of over-consumers. We focus on two classes of concerns: sensitivity to calibration choices and measurement error. Overall, these analyses suggest the wedges are not primarily driven by measurement error or preference heterogeneity and vary intuitively with the choice of preference parameter inputs.

4.3.1 Sensitivity Analysis

We vary the value of each input parameter (β, γ, and the nondurable share of $\frac{C}{Y}$) and recalculate the distribution of wedges to assess the sensitivity of our results to these calibration choices. We summarize the resulting share of over-consumers and the median absolute value wedge in Table 2 and the full relationships between the inputs and results in Figures F.1 to F.4.

Table 2. Sensitivity Analysis: Impact of Alternative Calibration Choices

	Parameter Range			Overconsumer (%)		P50 Abs(Wedge) (%)	
	Calibration (1)	Min (2)	Max (3)	Min (4)	Max (5)	Min (6)	Max (7)
β	0.92	0.80	0.98	18.5	73.7	40.3	53.6
γ	2.00	1.00	5.00	49.5	51.7	37.1	60.8
Nondurable share of $\frac{C}{Y}$	0.7937	0.72	0.90	42.4	57.4	39.4	43.3

Notes: Table presents the sensitivity of two results to our parameter calibration: (1) the percent of users who overconsume and (2) the median absolute value wedge. Under the "Parameter Range" heading, the "Calibration" column shows our baseline calibrated value and the "Min" and "Max" columns show the range of values that we test. Under the "Overconsumer (%)" and "P50 Abs(Wedge) (%)" headings, the "Min" and "Max" columns show the minimum and maximum value of each result that we get across each parameter range. When we vary one parameter, we hold all other parameters at their baseline calibrated values.

Discount Factor (β). We begin by varying our choice of annual discount factor (β) from 0.80 to 0.98. Figure F.1 displays the results. Naturally, the discount factor has a significant effect on the frictionless benchmark: if a consumer heavily discounts future consumption, their frictionless consumption today is significantly higher, leading to lower wedges. Relative to our benchmark calibration of 0.92, a β of 0.80 decreases the share of over-consumers from 51% to 18.5% while a β of 0.98 increase the share of over-consumers to 73.7%. The median absolute value of the wedge is less sensitive because in either case it combines the wedges on one side of the distribution becoming larger while attenuating those on other side. These results provide some reassurance that the frictionless benchmark and resulting wedges behave as we would expect for a given level of actual consumption, and there remains a substantial share of over-consumers even when everyone is assumed to have extremely low discount rates.

Inverse Intemporal Elasticity of Substitution (γ). We next examine alternative choices for the coefficient of relative risk aversion/inverse IES (γ). We vary γ from one to five and display the results in Figure F.2. The share of over-consumers remains close to 51%, while the median absolute value wedge slightly decreases with γ.

Non-Durable Expenditure Share. The last calibration parameter we vary is the non-durable expenditure share. Our calibrated value is 79.37% (obtained from Beraja and Zorzi, 2024). In our sensitivity analysis, we vary it from 72-90%, which more than spans the range of other values reported in the literature.[12] In contrast to β and γ, the non-durable expenditure share does not affect the frictionless benchmark but does affect the measurement of total actual APC. We scale observed non-durable APCs by the non-durable expenditure share to infer total APCs, therefore lower assumed non-durable expenditure shares translate to larger total APCs and higher shares of over-consumers. This monotonic relationship is observable in Figure F.4 and Table 2, which shows that the share of over-consumers ranges from 42.4% to 57.4% when we shift the non-durable expenditure share from 0.72 to 0.90. As above, the median absolute value wedge is broadly insensitive to the calibration choice.

Preference Heterogeneity. If consumers have heterogeneous preferences, the difference between an individual's true preference parameter and the homogeneous calibrated value used in our baseline analysis would contribute to their consumption wedge. Hence preference heterogeneity could

[12] This choice of range is motivated by other estimates of this expenditure share in the literature. Estimates in Ganong and Noel (2019) using transactions data imply values of 77-85%. Laibson et al. (2022) estimate a value close to 87.5% from aggregate spending data. We obtain a value of 88.8% when we classify durable expenditure in the EarnIn transactions data.

also be a source of consumption wedges in our analysis. We assess the sensitivity of our results to a model with three heterogeneous types, using the three preference types estimated in Aguiar et al. (2024).[13] For each person in our sample, we assign them the discount factor and risk aversion type that minimizes the absolute value of their consumption wedge. This three-type model of preference heterogeneity reduces the wedges modestly: the median absolute value of the wedges declines from 40% to 37%, and the share of over-consumers falls from 51% to 39% (Figure F.3). This analysis implies that our results remain similar in the presence of plausible levels of preference heterogeneity.

4.3.2 Measurement Error

Subgroups with Milder Measurement Error. We begin by studying subgroups where measurement error is plausibly milder. This helps gauge the plausibility that our results are sensitive to measurement error. Appendix F.1 details the groups that we consider. Examples include dropping users with UI income that, despite the phrasing of our survey questions, may not have included growth in UI in their income growth forecasts.[14] Another analysis omits users who answered one or more financial literacy questions incorrectly.[15] Such users may have a more difficult time communicating their economic expectations. Similarly, we also drop users whose reported inflation expectations are multiples of five, as such responses may be rounded. We also consider several subgroups related to consumption measurement error. One example includes users whose peer-to-peer transfers exceed 25% of nondurable spending in at least one month. Such users may have significant spending that we do not capture. Figure F.7 reports results from excluding these various subgroups. The share of over-consumers remains similar, generally ranging from 40-55%. The median absolute value consumption wedge varies slightly, ranging between 37-41%.

Grouping Users. Suppose that measurement error in beliefs, consumption, income, and wealth is mean zero across sufficiently "similar" users. One could then group these similar users, calculate representative measures of the consumption wedge inputs, and calculate a representative consumption wedge for each group. By averaging (or taking the median) across wedge inputs, such measurement error could be reduced.

To implement this, we group respondents using k-prototype clustering, which is a combination of k-means and k-modes clustering (for more details on the algorithm, see Appendix F.1). We

[13] In practice, any feasible consumption choice can be rationalized by some set of preference parameters. Therefore, a model with unconstrained individual-level heterogeneity cannot generate consumption wedges: any observed consumption data can be inverted to generate the set of preferences that rationalize those individual choices.

[14] 175 users in our sample (3%) have at least one month of UI income in the pre-survey period.

[15] These responses could indicate either low financial literacy or inattention during the survey.

group respondents based on their similarity in terms of reported age, annual income, savings, and indicators for gender, race, relationship status, presence of children, college education, and political affiliation.[16] We construct 500 clusters, resulting in 12 observations per cluster on average. Figure F.8 displays updated histograms. The share of over-consumers increases to 58%. The median absolute value wedge falls to 17%. These reductions likely not only reflect decreases in measurement error but also attenuation to mixing over-consumers and under-consumers These smaller wedges may be the result of attenuation due to being more likely to aggregate wedges across over- and under-consumers as cluster size grows.

4.4 Validation and Interpretation: Evidence from Wedge Correlates

We next examine how consumption wedges vary with observable characteristics. This analysis serves two purposes. First, by showing that wedges vary intuitively with users' hypothetical and actual behavior, this provides validating evidence that consumption wedges plausibly relate to the distortions that shape consumption. Second, our findings provide suggestive evidence on *which* distortions are driving the wedges.

MPCs. Here we explore the relationship between consumption wedges and MPCs. If financial constraints are the dominant distortion to consumption and the mechanism behind high MPCs, we would expect to see the highest MPCs for the most negative consumption wedges. To test this, we use the transactions data to measure individual-level MPCs based on consumers' non-durable spending responses to the March 2021 stimulus payments. These checks provided $1,400 to each eligible individual, with an additional $1,400 for each dependent.[17] Approximately 68% of the survey analysis sample received a stimulus check. We determine each user's stimulus payment date and amount from the transactions data. For each user, we examine consumption from 28 days before to 27 days after the stimulus check was received. Days -27 through -1 are the "pre" period, and days 0 through 27 are the "post" period. We then use the same date ranges in 2022, 2023, and 2024 as comparison periods. We calculate each individual's MPC as follows:

$$MPC_i = \frac{1}{StimulusAmount_i} \times (\Delta Spend_i^{2021} - \frac{\Delta Spend_i^{2022} + \Delta Spend_i^{2023} + \Delta Spend_i^{2024}}{3}) \tag{7}$$

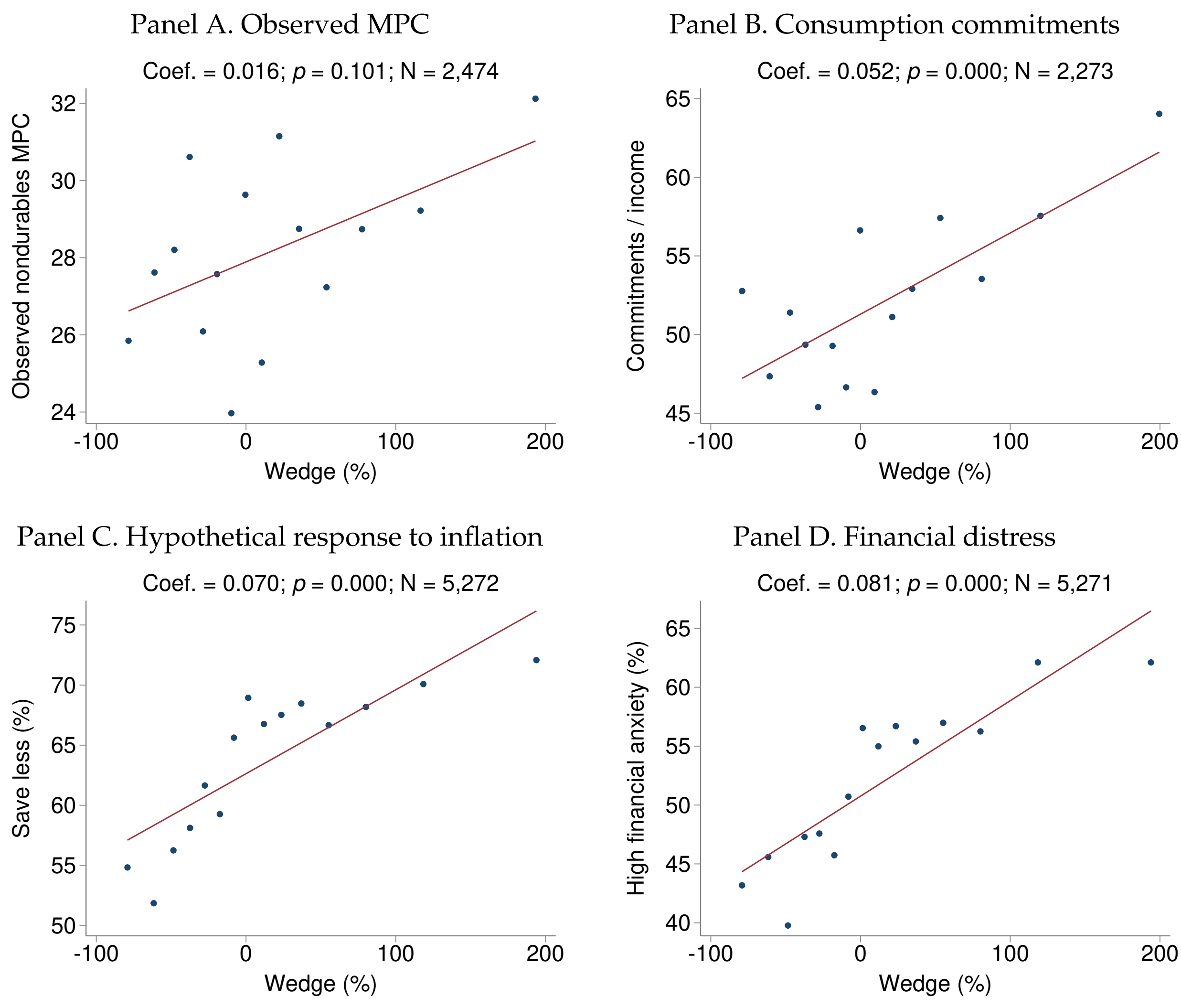
where

$$\Delta Spend_i^t = Spend_i^{Post,t} - Spend_i^{Pre,t} \tag{8}$$

[16] We z-score continuous variables so that they exert equal influence in cluster assignment.
[17] The stimulus payment dates range from March 12, 2021 to May 28, 2021.

Our MPC measure captures the "excess" consumption associated with receipt of the stimulus check. We note that this measure should be interpreted as at best a proxy for an individual's MPC, as we only have three observations per person. As such, this measure is unlikely an asymptotically valid estimate of the individual's true MPC. The median estimated MPC is 25%. There are a few extreme outliers (e.g., below -500% or above 500%), likely due to large, one-time purchases. Given this feature of the data, we trim MPCs at the 10th and 90th percentiles.

Figure 3. Relationship Between Consumption Wedges and Nondurable MPCs



Notes: The figure illustrates the relationship between dynamic consumption wedges and observed nondurable MPCs, consumption commitments (% income), an indicator for whether the user would hypothetically "save less" in response to higher inflation, and an indicator for whether the user reports "high" or "very high" financial anxiety. The binned scatterplot plots the average value within quantile-based intervals of consumption wedges. Variable definitions are outlined in Appendix C.4. MPCs are observed for 58% of users in our analysis sample. Wedges are trimmed at the 1st and 95th percentiles and MPCs are trimmed at the 5th and 95th percentiles.

Figure 3 Panel A displays a binscatter comparing individuals' MPCs against their consumption wedges. As consumption wedges increase, we observe larger MPCs on average. A 25 pp larger wedge is associated with a 0.4 pp larger MPC. A limitation of our MPC measure is that it is measured for a check received 1.5 to 3.5 years before our surveys (conducted between September 2022 and November 2024). The relationship we measure likely understates the relationship one would find if able to instead use a contemporaneous MPC measure.

These results have two implications. The first is as a validation, showing that consumption wedges are strongly related to the behavioral responses of consumption. The second is that higher MPCs are associated with over-consumption, rather than the under-consumption. This suggests that the forces underlying high MPCs among low-liquidity households are predominantly attributable to forces that generate positive wedges, such as present bias and consumer inertia, rather than financial constraints.

Consumption Commitments. The insufficiency of financial constraints alone to rationalize the distribution of consumption wedges naturally raises the question of which distortions can best explain deviations from the benchmark. In survey waves 2 and 3, we asked consumers for their monthly housing and childcare costs as a measure of their "committed consumption," as these expenses tend to be large, difficult to adjust, and difficult to identify in transactions data. We divide these reported monthly expenditures by average monthly income over the preceding twelve months (i.e., July 2023 to June 2024 for July 2024 respondents), as measured in the transactions data. We interpret a high value of this ratio as a consumer having a high share of committed consumption. Figure 3 Panel B shows a strong positive relationship between wedges and consumption commitments. A 25 pp larger wedge is associated with a 1.3 pp higher ratio of committed consumption to income. This pattern suggests consumption commitments are a plausible friction behind the consumption wedges we measure.

Hypothetical Spending/Saving Behavior. Our survey also presents consumers with a hypothetical scenario that asks how they would adjust their saving behavior in response to higher expected inflation. The majority of respondents report that they would "save less" when future inflation is higher, and Figure 3 Panel C shows that this response is also positively correlated with the consumption wedges. The survey also solicited rationales for respondents' hypothetical savings behavior. Among respondents selecting "save less," a large majority (86%) attributed this dissaving to an *inability* to reduce spending. These results suggest an intuitive relationship between consumers' mental model of their own behavior and the wedges we estimate using their economic beliefs and actual consumption choices. This explanation most naturally relates to consumer inertia and provides some suggestive corroboration for the consumption commitments result.

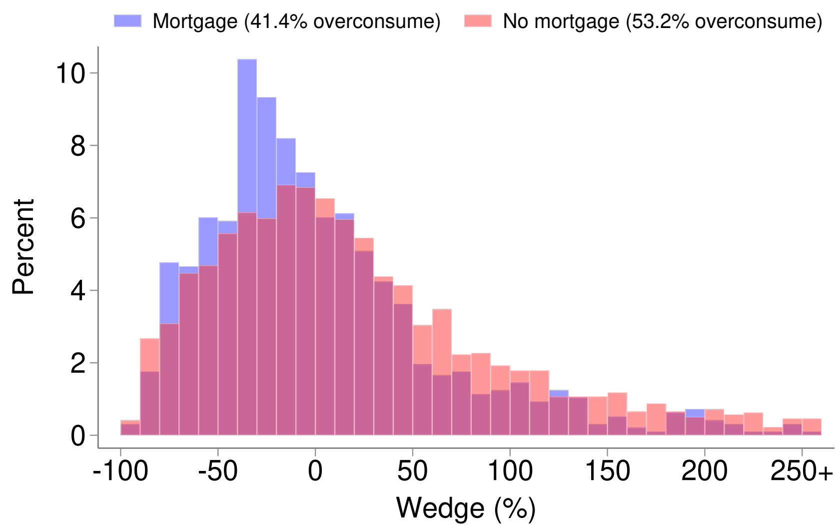
Financial Distress Proxies. We next examine how wedges vary with proxies for financial distress. These include subjective measures, such as ratings of anxiety about finances or the manageability of one's debt. We also use objective measures such as having savings account balances below $500 most of the time. We report the correlation with financial anxiety in Figure 3 Panel D and the remaining correlations in Appendix Figure A.3. For all measures we consider, we find a strong, positive relationship between consumption wedges and financial distress.

Not only is financial distress more common among over-consumers, but it is also rarer among under-consumers with larger (in magnitude) wedges. One possible rationalization for this phenomenon relates to wealthy hand-to-mouth households, as in Kaplan and Violante (2014). Households able to accumulate substantial illiquid assets, like homes or retirement savings, are likely less financially distressed than those that struggle to acquire such assets. At the same time, constraints on their ability to borrow against this illiquid wealth may significantly distort their consumption downwards. The size of the distortion induced by these constraints is larger, all else equal, when the value of illiquid assets is greater. Hence, households with large to moderate negative distortions may on average be less financially distressed than those that are less able to acquire illiquid assets. Households that are both house- and cash-poor may lack the necessary collateral to be as exposed to financial constraints as the wealthy hand-to-mouth. This suggests that financial constraints is a better model for the wealthy hand-to-mouth households compared to the poor hand-to-mouth. Instead, present bias or consumer inertia is more likely the dominant friction affecting households with low liquid wealth.

The positive association between over-consumption and financial distress suggests that the underlying frictions or behavioral preferences driving over-consumption are linked with lower wellbeing. Policymakers concerned with alleviating financial distress may therefore be better able to achieve this goal if policy is informed by theories of consumer behavior that feature over-consumption.

Homeownership. Motivated by our results regarding financial distress, we next compare wedges across homeowners and non-homeowners. We proxy for homeownership with whether the respondent has a mortgage. We find that homeowners on average plausible resemble the financially constrained "wealthy hand-to-mouth" households of Kaplan and Violante (2014). A majority of homeowners have negative wedges. Over-consumption is 30% more common among non-homeowners (53% versus 41%). This is consistent with financial constraints being the dominant distortion for households with substantial illiquid wealth.

Figure 4. Distribution of Consumption Wedges by Mortgage Possession



Notes: The figures show the distribution of dynamic consumption wedges, separately for users that have a mortgage (18% of the sample) and those that do not have a mortgage (82%). The share of overconsumers for each subgroup is shown in the figure legend. Wedges are trimmed at the 1^{st} and 95^{th} percentiles.

5 Conclusion

This paper introduces a novel approach to measure individual-level distortions to consumption. We use a new dataset that links surveyed economic expectations to administrative transactions data for a sample of households that skews low-liquidity and middle-income. We measure the impact of distortions (frictions or behavioral preferences) as a wedge between actual consumption and a counterfactual "frictionless" benchmark. Our benchmark allows households to deviate from full-information rational expectations (FIRE), so that the wedge isolates the influence of frictions and behavioral preferences separately from deviations from FIRE. This is an important innovation to wedge measurement, as there generally exists some set of beliefs that can rationalize behavior that could otherwise be explained by frictions or behavioral preferences. Because our benchmark is a special case in a large class of models, our approach makes it possible to measure the total impact of distortions on consumption due to a wide variety of frictions or behavioral preferences.

Our main findings indicate that distortions play an important role in driving household consumption and call into question the dominant role played by financial constraints in explaining the consumption of low-liquidity households. Most households have large distortions in our sample; the median (absolute value) distortion stands at 40% of frictionless consumption. The average distortion is 16%, but this belies significant heterogeneity in the cross section. In particular, there is a mix of positive and negative wedges. 51% of wedges are positive (over-consumption) while the remaining 49% are negative. Because financial constraints can only generate negative wedges, the 51% of over-consumers cannot be explained by financial constraints. Additional or alternative mechanisms are necessary to explain the consumption choices of low-liquidity households. We identify two promising alternatives. A combination of financial constraints and present bias could potentially generate a similar distribution of wedges, as present bias creates positive wedges. Additionally, consumer inertia (e.g., consumption commitments) can give rise to both positive and negative wedges. Correlating wedges with MPCs, financial distress proxies, homeownership, and proxies for consumption commitments further suggests the two alternative models hold promise to better explain the consumption choices of low-liquidity households.

We outline several directions for future research. Future research could use surveys alone (or in conjunction with administrative transactions data) to measure wedges in other settings. Measuring wedges for consumers at different lifecycle stages or in a broader population would be especially valuable. One could also use such measures to document other correlations or possibly estimate the causal effect of various shocks (such as monetary policy or stimulus check receipt) on wedges. Such evidence could help further guide the design of theories of consumer behavior. Our findings of large wedges indicate the importance of incorporating frictions or behavioral preferences into such theories. Another valuable direction for future research would be to study the wedges produced by quantitative structural models and to compare wedges for low-liquidity households with those that we find. Such evidence would help test competing models of frictions and behavioral preferences. Additionally, moments from the wedge distribution we estimate could also be used to calibrate such models, disciplining the quantitative features of the frictions or behavioral preferences present. Lastly, our findings suggest that it is important to devote more attention to distortions other than financial constraints.

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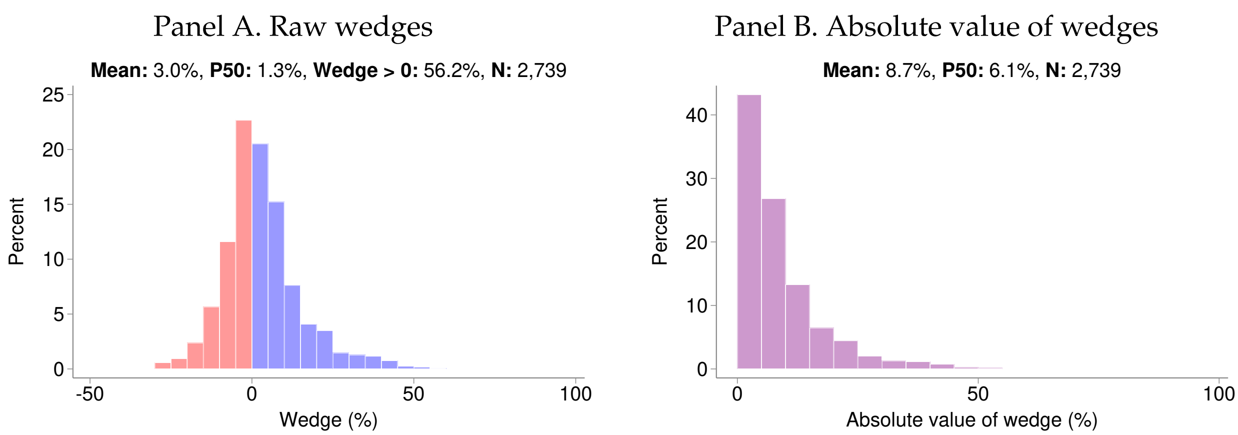
Appendix

Contents

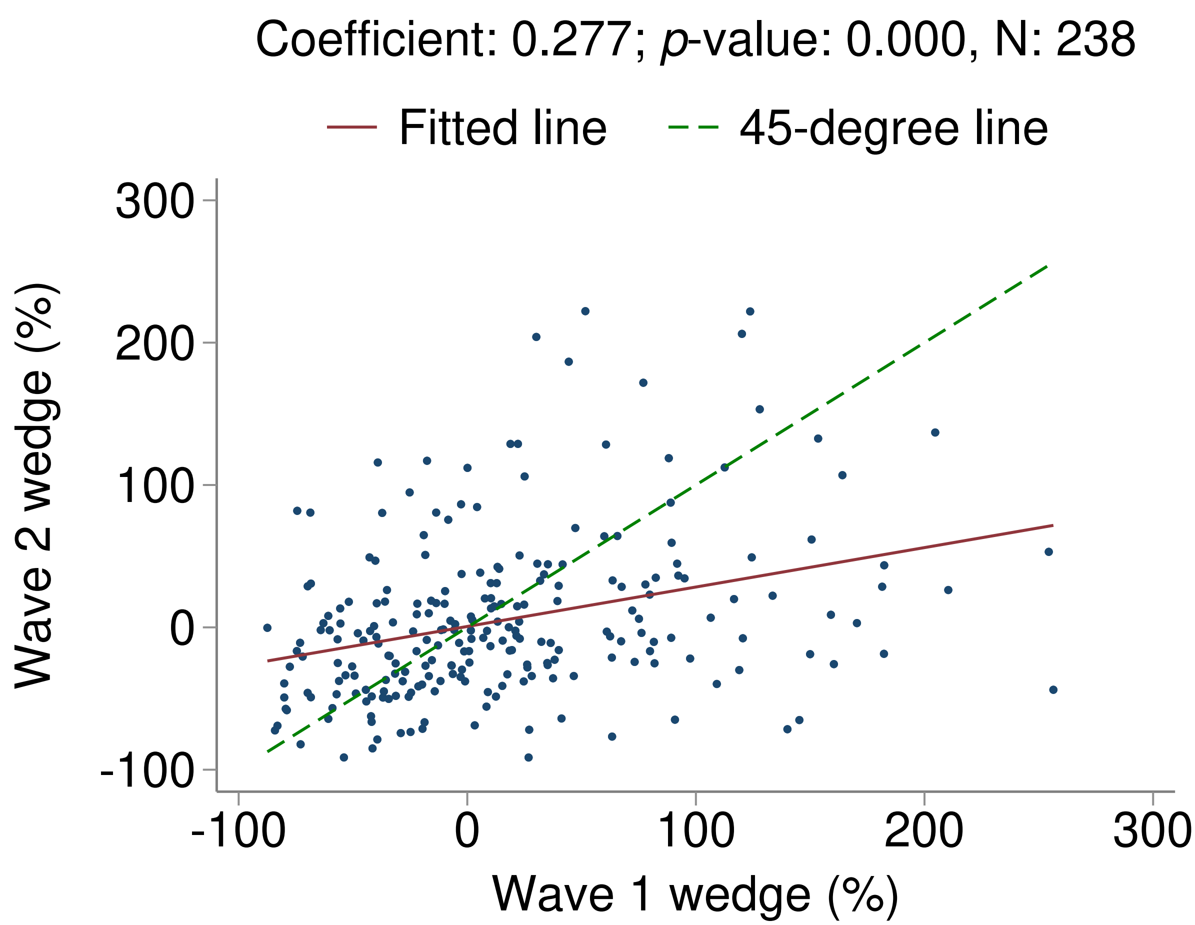
A Appendix Figures

Figure A.1. Distribution of Static Consumption Wedges



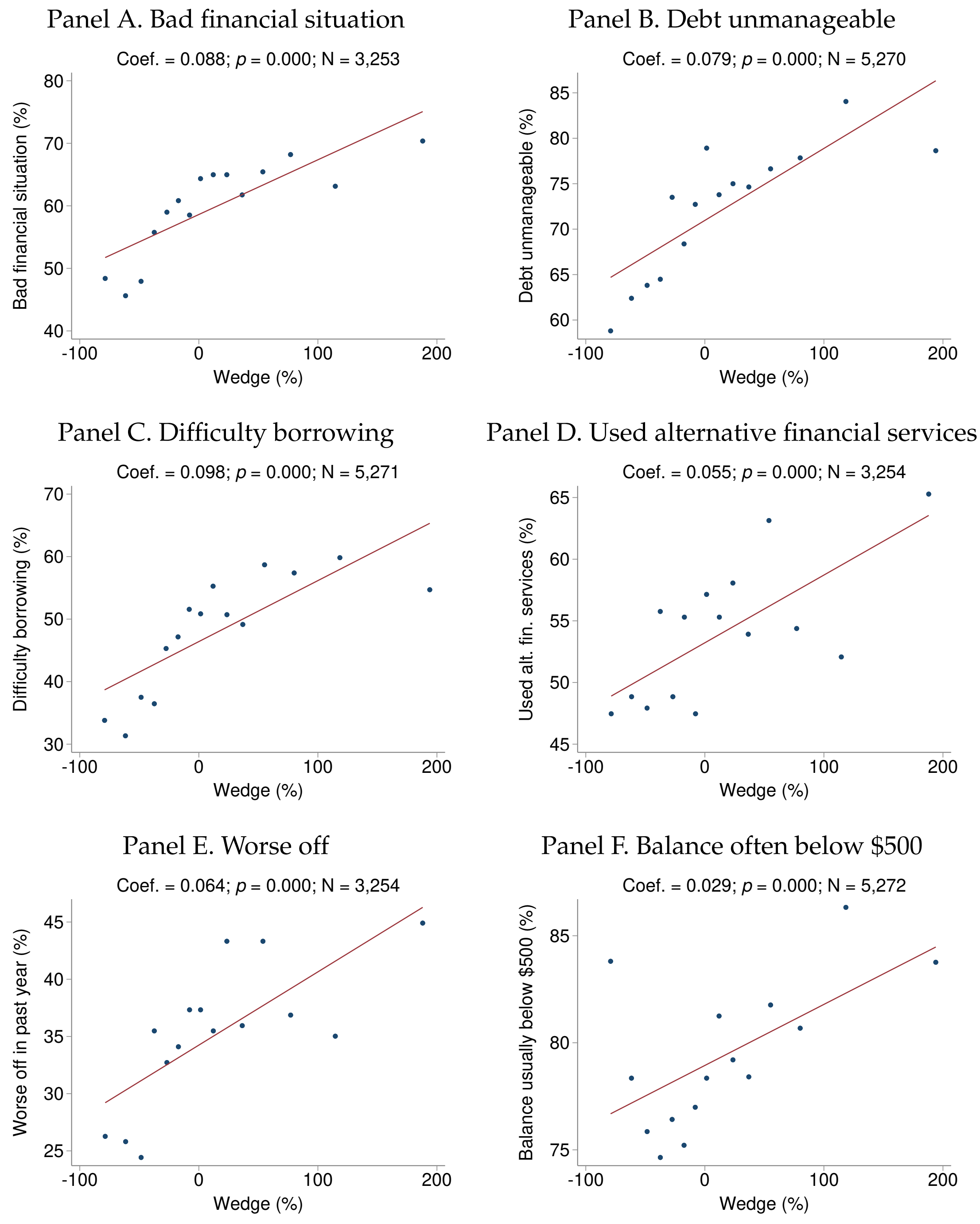
Notes: The figures show the distribution of static consumption wedges (left) and their absolute values (right). Wedges are trimmed at the 1^{st} and 99^{th} percentiles. Includes users from waves 2 and 3 only, as we did not solicit spending growth expectations (an input to the static wedges) in wave 1.

Figure A.2. Relationship Between Wave 1 and Wave 2 Wedges



Notes: The figure illustrates the relationship between dynamic consumption wedges in wave 1 and wave 2, restricting to users who completed wave 2. The solid red line represents a linear fitted line, and the dashed green line represents a 45-degree line. The coefficient and p-value from a regression of wave-2 wedges on wave-1 wedges are shown at the top of the figure. Wedges are trimmed at the 1^{st} and 95^{th} percentiles.

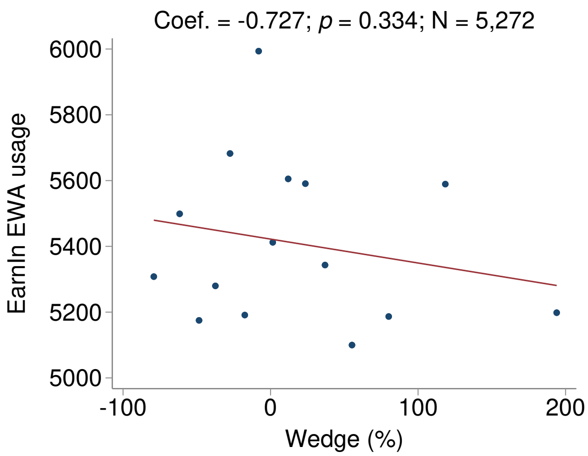
Figure A.3. Relationship Between Dynamic Consumption Wedges and Financial Distress



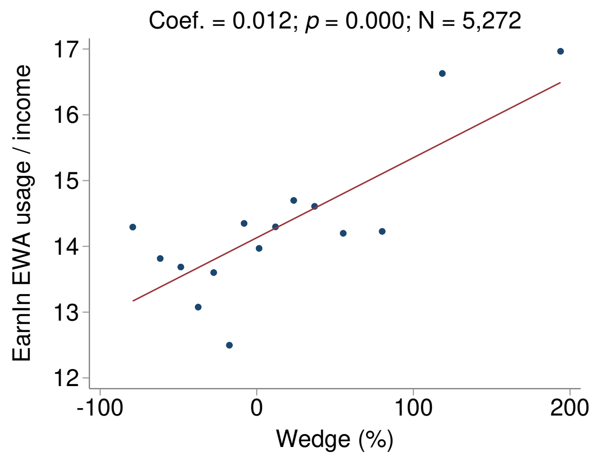
Notes: The figures illustrate the relationship between dynamic consumption wedges and six indicators of financial distress: (1) whether the user reports "just getting by" or "finding it difficult to get by;" (2) whether the user reports having "a bit more" or "far more" debt than is manageable; (3) whether the user reports difficulty borrowing due to "often" or "most of the time" being denied for credit; (4) whether the user reports using alternative financial services in the past 3 months (wave 1 only); (5) whether the user reports being "somewhat" or "much" worse off financially compared to 12 months ago; and (6) whether the user's observed balances are below $500 for more than 50% of the pre-survey period. Each binned scatterplot plots the average value of the financial distress indicator within quantile-based intervals of consumption wedges. Wedges are trimmed at the 1st and 95th percentiles.

Figure A.4. Relationship Between Dynamic Consumption Wedges and EarnIn EWA Usage

Panel A. EarnIn EWA usage ($)



Panel B. EarnIn EWA usage (% income)



Notes: The figures illustrate the relationship between dynamic consumption wedges and two measures of EWA usage over the 12 months preceding the survey: (1) the dollar amount of EarnIn EWA outflows and (2) the ratio of EarnIn EWA outflows to income. Each binned scatterplot plots the average value of the EWA usage variable within quantile-based intervals of consumption wedges. Wedges are trimmed at the 1st and 95th percentiles.

B Theory Derivations and Extensions

B.1 Frictionless Consumption Derivation

We approximate frictionless consumption using first-order approximation of the style $f(x) \approx f[\widetilde{E}_t(x)] + f'[\widetilde{E}_t(x)][x - \widetilde{E}_t(x)]$, which yield $\widetilde{E}_t[f(x)] \approx f[\widetilde{E}_t(x)]$. We begin by approximating the Euler equation.

Lemma 1: Euler Equation Approximation

In the frictionless benchmark, the one-period-ahead and multi-period Euler equations are approximately

$$C_t^\star \approx \frac{\widetilde{E}_t C_{t+1}}{\widetilde{E}_t \pi_{t+1}} \left(\beta \frac{\widetilde{E}_t R_{t+1}}{\widetilde{E}_t \pi_{t+1}} \right)^{-1/\gamma}$$
$$C_t^\star \approx \widetilde{E}_t C_{t+j} \prod_{k=1}^{j} \left[\frac{1}{\widetilde{E}_t \pi_{t+k}} \left(\beta \frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{-1/\gamma} \right],$$

where $\gamma = -\frac{u''(c_t^\star)}{u'(c_t^\star)} c_t^\star$, is the inverse IES/coefficient of relative risk aversion evaluated at time t frictionless consumption $c_t^\star$.

Proof. Taking a first-order approximation of the Euler equation

$$u'\left(\frac{C_t^\star}{P_t}\right) = \beta \widetilde{E}_t \left[u'\left(\frac{C_{t+1}}{P_{t+1}}\right) \frac{R_{t+1}}{\pi_{t+1}} \right]$$

yields

$$u'\left(\frac{C_t^\star}{P_t}\right) \approx \beta u'\left(\frac{\widetilde{E}_t C_{t+1}}{\widetilde{E}_t P_{t+1}}\right) \frac{\widetilde{E}_t R_{t+1}}{\widetilde{E}_t \pi_{t+1}}.$$

Under CRRA preferences, $u'(c) = c^{-\gamma}$, and we can rearrange the above to obtain:

$$C_t^\star \approx \frac{\widetilde{E}_t C_{t+1}}{\widetilde{E}_t \pi_{t+1}} \left(\beta \frac{\widetilde{E}_t R_{t+1}}{\widetilde{E}_t \pi_{t+1}} \right)^{-1/\gamma}.$$

Under non-CRRA preferences, we obtain the same expression using the a log-linear first-order approximation of the marginal utility function below:

$$\ln\left[u'(c)\right] \approx \ln\left[u'(\bar{c})\right] + \frac{u''(\bar{c})}{u'(\bar{c})} \bar{c} \left(\ln c - \ln \bar{c}\right)$$
$$\ln\left[\frac{u'(c)}{u'(\bar{c})}\right] \approx -\gamma \left(\ln c - \ln \bar{c}\right)$$
$$\frac{u'(c)}{u'(\bar{c})} \approx \left(\frac{c}{\bar{c}}\right)^{-\gamma}.$$

The second line uses $\gamma = -\frac{u''(\bar{c})}{u'(\bar{c})} \bar{c}$. For the approximate Euler equation, γ is evaluated at (real) frictionless consumption: $\gamma = -\frac{u''(c_t^\star)}{u'(c_t^\star)} c_t^\star$.

The derivation for the multi-period Euler equation:

$$u'\left(\frac{C_t}{P_t}\right) = \widetilde{E}_t \left[\beta^j u'(c_{t+j}) \prod_{k=1}^{j} \frac{R_{t+j}}{\pi_{t+j}}\right]$$

is analogous, yielding:

$$C_t^\star \approx \widetilde{E}_t C_{t+j} \prod_{k=1}^{j} \left[\frac{1}{\widetilde{E}_t \pi_{t+k}} \left(\beta \frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}}\right)^{-1/\gamma}\right].$$

□

We next take a first-order approximation of the forward-iterated budget constraint.

Lemma 2: Budget Constraint Approximation

Under a no-Ponzi condition, $\lim_{j\to\infty} \frac{A_{t+j}}{R_{t+1}\cdots R_{t+j-1}} = 0$, *the expected forward-iterated budget constraint is approximately:*

$$C_t^\star \approx A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t G_{t,t+j}}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}}\right) - \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t C_{t+j}}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}}\right)$$

where $G_{t,t+j}^Y = \frac{Y_{t+j}}{Y_t}$ *is the gross nominal growth rate of income from period* t *to period* $t+j$.

Proof. We begin with the period t budget constraint:

$$C_t^\star + A_{t+1} = Y_t + A_t R_t.$$

We then forward iterate the budget constraint and apply the no-Ponzi condition:

$$C_t^\star = A_t R_t + Y_t + \sum_{j=1}^{T} \frac{Y_{t+j}}{\prod_{k=1}^{j} R_{t+k}} - \sum_{j=1}^{T} \frac{C_{t+j}}{\prod_{k=1}^{j} R_{t+k}}.$$

Next, we rewrite income in terms of cumulative income growth rates $Y_{t+j} = Y_t G_{t,t+j}^Y$:

$$C_t^\star = A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \frac{G_{t,t+j}^Y}{\prod_{k=1}^{j} R_{t+k}} - \sum_{j=1}^{T} \frac{C_{t+j}}{\prod_{k=1}^{j} R_{t+k}}.$$

And then we take expectations:

$$C_t^\star = A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \widetilde{E}_t \left(\frac{G_{t,t+j}^Y}{\prod_{k=1}^{j} R_{t+k}}\right) - \sum_{j=1}^{T} \widetilde{E}_t \left(\frac{C_{t+j}}{\prod_{k=1}^{j} R_{t+k}}\right)$$

and then a first-order approximation:

$$C_t^\star \approx A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t G_{t,t+j}^Y}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}} \right) - \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t C_{t+j}}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}} \right).$$

$\square$

Our next proposition derives our characterization of frictionless consumption using the approximation from the preceding lemmas.

Proposition 1: Frictionless Consumption

Combining the approximations from Lemmas 1 and 2, we can characterize (approximate) frictionless consumption as follows:

$$C_t^\star \approx \frac{A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left[\widetilde{E}_t G_{t,t+j}^Y \prod_{k=1}^{j} \left(\widetilde{E}_t R_{t+k} \right)^{-1} \right]}{1 + \sum_{j=1}^{T} \left\{ \prod_{k=1}^{j} \left[\beta^{1/\gamma} \left(\frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{1/\gamma - 1} \right] \right\}}.$$

Proof. We begin with the approximate Euler equation from Lemma 1. We rearrange it to write it in terms of expected future consumption:

$$\widetilde{E}_t C_{t+j} \approx C_t \prod_{k=1}^{j} \left[\widetilde{E}_t \pi_{t+k} \left(\beta \frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{1/\gamma} \right].$$

Using the above expression, we substitute in for $\widetilde{E}_t C_{t+j}$ in the approximate budget constraint equation from Lemma 2:

$$\begin{aligned} C_t^\star &\approx A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t G_{t,t+j}^Y}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}} \right) - \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t C_{t+j}}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}} \right) \\ &= A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left(\frac{\widetilde{E}_t G_{t,t+j}^Y}{\prod_{k=1}^{j} \widetilde{E}_t R_{t+k}} \right) - C_t^\star \sum_{j=1}^{T} \left\{ \prod_{k=1}^{j} \left[\beta^{1/\gamma} \left(\frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{1/\gamma - 1} \right] \right\} \\ &= \frac{A_t R_t + Y_t + Y_t \sum_{j=1}^{T} \left[\widetilde{E}_t G_{t,t+j}^Y \prod_{k=1}^{j} \left(\widetilde{E}_t R_{t+k} \right)^{-1} \right]}{1 + \sum_{j=1}^{T} \left\{ \prod_{k=1}^{j} \left[\beta^{1/\gamma} \left(\frac{\widetilde{E}_t R_{t+k}}{\widetilde{E}_t \pi_{t+k}} \right)^{1/\gamma - 1} \right] \right\}}. \end{aligned}$$

$\square$

B.2 Extension: Durable and Non-Durable Goods

We next show how to extend our wedge measurement results to accommodate durable goods. Durable goods present several complications: it's difficult to measure their consumption and depreciation directly, holdings of durable goods constitute a source of wealth, and some are financed with debt. To overcome these challenges, we make assumptions that imply that the expenditure share of non-durable goods is a constant, known fraction. The key assumption is that notional consumption is a Cobb Douglas aggregate of both types of consumption goods.

Notation. Let n_t and d_t denote real period t consumption flows of non-durable and durable goods (respectively). We continue to denote the total nominal value of net worth by A_t. Total wealth includes net positions in durables (e.g., the value of vehicles net of the loans used to finance their purchase). The household has preferences over notional consumption flows c_t, which are an aggregate of non-durable and durable consumption flows (i.e., utility $u(c_t)$ is the per-period utility flow). We make two assumptions.

Assumption 1: Frictionless Spot and Rental Markets for Durables and No Arbitrage.

In our frictionless benchmark, the household can frictionlessly buy or sell durables at a spot price. The household can also rent durable goods at a per period rental price of q_t. No arbitrage in the durable goods markets requires that the rental price q_t equal the user cost of the durable goods.

By assuming that households can frictionlessly transact in our benchmark, the wedge we estimate is able to capture frictions on adjusting the stock of durables. The no arbitrage assumption means that the household is indifferent between holding and accumulating durables versus renting them. This allows us to simplify our exposition while keeping the user cost of durables flexible. The user cost reflects depreciation, forgone interest earnings/savings, and appreciation of durable goods prices.

We let non-durables, n_t, be the numeraire good. Under Assumption 1, we can write the household's budget constraint simply as

$$A_{t+1} + P_t c_t = Y_t + A_t R_t$$

where

$$P_t c_t = n_t + q_t d_t.$$

and P_t is the ideal price index. The budget constraint is isomorphic to our original budget constraint. The Euler equation remains unchanged as well, where c_t now corresponds to notional consumption. Therefore, the intertemporal optimality conditions presented in Section 2 remain unchanged. There are now simply additional first order conditions for intratemporal optimality with respect to the allocation of spending between non-durable and durable consumption.

Assumption 2: Cobb Douglas Aggregation.

The household's notional consumption good is a Cobb Douglas aggregate of non-durable and durable consumption flows:

$$c_t = n_t^{\alpha} d_t^{1-\alpha}.$$

Under Assumptions 1 and 2, the intratemporal optimality conditions are:

$$\begin{aligned} n_t &= \alpha P_t c_t \\ d_t q_t &= (1-\alpha) P_t c_t. \end{aligned}$$

The intratemporal optimality conditions indicate that expenditure on each good is a constant share of total expenditures on consumption goods. As a result, we can infer nominal notional consumption C_t from nominal non-durable consumption n_t and the expenditure share α. This is formalized in the lemma below.

Lemma 3: Consumption Calculation Including Consumption of Durables

Under Assumptions 1 and 2, notional consumption C_t is

$$C_t = P_t c_t = \frac{n_t}{\alpha}$$

where α corresponds to the non-durable share of expenditures.

In our baseline analysis, in order to characterize deviations in notional consumption, we multiply non-durable consumption by an estimate of $\frac{1}{\alpha}$.

C Data Construction

C.1 Transactions Data

C.1.1 Data Structure

We receive anonymized data from EarnIn that covers user-level information, bank transactions, daily checking and savings account balances, and transactions classified as earnings. All data are de-identified and stored on secured servers. The dataset spans January 2021 through November 2024, covering at least 12 months before each survey wave. Users remain in the dataset until they either delete their accounts or disconnect their linked bank account. Among the users in our analysis sample, 97% had at least one EWA cashout in the 12 months preceding the survey, with a median annual cashout amount of approximately $4,700.

User-Level Data. We receive, weekly, user-level datasets that include both time-invariant variables (e.g., EarnIn sign-up date) and time-varying variables (e.g., number of hours worked in the last 7 days). These tags are merged into each of the other datasets.

Balances. The balances dataset provides daily records of the number and total balances of checking, savings, and "other" bank accounts linked to EarnIn. We do not observe balances for unlinked bank accounts or investment accounts.

Transactions. The transactions dataset includes transaction-level records with the transaction date, dollar amount, a memo describing the source or destination, and a transaction category assigned by Plaid, a third-party service that connects users' bank accounts to EarnIn. We do not observe transactions associated with unlinked bank accounts or credit cards.

Earnings. The earnings dataset is a direct subset of the transactions dataset, limited to earnings inflows from jobs reported to EarnIn. Each record includes the payment date, posted date, dollar amount, and whether those earnings are from unemployment benefits. Earnings are observed net of taxes and payroll deducations when deposited into users' linked bank accounts; we do not receive information on gross pay or withheld amounts.

C.1.2 Categorizing Transaction Inflows

We leverage the transactions and observed earnings datasets to construct a measure of income, which we define as the sum of post-tax labor earnings and unemployment insurance (UI).

We start by cleaning transaction memos to remove any non-alphabetic characters. This helps us aggregate transactions from the same source, even where memos include dates of payment.

To identify transactions as UI payments, EarnIn maintains a list of transaction memos that indicate whether an inflow is UI-related. We supplement this list with other memos that we identify as attached to UI payments.

To identify transactions as earnings, we first compare transaction amounts to EarnIn's observed earnings database, which includes weekly earnings by source for each individual. The database distinguishes different sources of earnings using three earnings variables. For example, if a user has only one source of earnings within a week, the first two earnings variable reflects the amount of earnings from each source, and the third earnings variable is missing. If we match a transaction inflow to the amount of one of these three observed earnings sources in a week, we consider those matched transactions to be earnings. If no match to a single transaction exists, we consider matches between observed earnings and the sum of transactions in a week with the same memo to be earnings. For a user with a matched memo, we also consider any other instance of that transaction memo to be earnings. We then track memos over the entirety of the database and consider a given memo to be earnings if it is tracked as earnings more than 5 times globally and is tracked as earnings over 90% of the time it appears.

Next, we perform straightforward searches of transaction memos. We flag any transaction with a memo containing the phrases "PAYROLL," "ACHPAY," "PAYRL," or "SALARY" as earnings.

Finally, we flag transactions that Plaid categorizes as Payroll or Income. Upon inspection, we find Plaid's categorization of Earnings and Income to be susceptible to false positives. To account for this, we require that the memo (1) occurs in more than two unique weeks with a modal frequency of every one or two weeks, (2) is not identified as unemployment benefits, and (3) either includes the phrase "DIRECT DEPOSIT" (or derivatives) or has a weekly amount between $50 and $5,000.

After this process, we drop hash IDs with more than five earnings in at least one week of the panel.

C.1.3 Categorizing Transaction Outflows

Our analysis focuses on nondurables spending. To construct this measure, we apply an outflows categorization algorithm that separates durables and nondurables spending from other types of outflows, including payments (e.g., interest and principal on loans, bank fees), internal transfers (i.e., transfers across checking, savings, or other accounts), and external transfers (i.e., transfers to other individuals or entities through Zelle, Venmo, or other platforms). This algorithm builds on the approaches of Ganong and Noel (2019) and Lusardi (1996), with modifications tailored to the structure of our data and the goals of our analysis.

The Plaid transaction taxonomy included in the EarnIn database comprises over 500 granular categories. We first map these categories to 33 broader categories that can be grouped under three overarching types: spending, payments, and transfers.

- **Spending:** Auto parts & repair, cash, department stores, discount stores, drug stores, digital entertainment, other entertainment, food services, gas stations, grocery stores, healthcare, home improvement, insurance, personal care services, professional services, taxis, transportation, travel, utilities, wholesale stores, other durables, other nondurables, other retail
- **Payments:** Auto loans, non-auto loans, buy now pay later, EarnIn earned wage access, other earned wage access, housing, overdraft & late fees, other payments
- **Transfers:** Checks, transfers across bank accounts, transfers to investment accounts, credit card payments, peer-to-peer transfers, other transfers

This mapping has three key limitations. First, Plaid's categorization is based on merchant types rather than the specific products and services purchased, making it difficult to distinguish between durables and nondurables in certain cases. For example, a transaction at a department store may include both a mattress (durable) and makeup (nondurable). Second, some Plaid categories are too broad or ambiguous to be mapped reliably, such as "Purchase," "Shopping," or "Transfer." Finally, we observe frequent misclassifications in Plaid's categorization.

To address the first limitation, we reallocate six spending categories that combine durables and nondurables: department stores, discount stores, drug stores, grocery stores, wholesale stores, and

Table C.1. Reallocation of Merchant Categories to Product Categories

Component of revenue	%	Mapped category	%
Panel A. Department stores			
Clothing	80%	Other nondurables	80%
Home products	10%	Home improvement	10%
Personal care products	10%	Other nondurables	10%
Panel B. Drug stores			
Personal care products	40%	Other nondurables	40%
Drugs	30%	Healthcare	30%
Retail nondurables	30%	Other nondurables	30%
Panel C. Discount stores			
Groceries	50%	Groceries	50%
Home products	15%	Home improvement	15%
Retail nondurables	15%	Other nondurables	15%
Drugs	10%	Healthcare	10%
Entertainment	10%	Other entertainment	10%
Panel D. Grocery stores			
Groceries	75&	Groceries	75%
Household supplies	25%	Other nondurables	25%
Panel E. Wholesale stores			
Groceries	60%	Groceries	60%
Electronics	15%	Other durables	15%
Personal care products	10%	Other nondurables	10%
Home appliances	10%	Other durables	10%
Healthcare	5%	Healthcare	5%
Panel F. Other retail			
Fashion	25%	Other nondurables	25%
Electronics & media	20%	Digital entertainment	20%
Toys, hobbies, & DIY	20%	Other durables	20%
Furniture & appliances	20%	Home improvement	20%
Food & personal care products	15%	Groceries	10%
Food & personal care products	15%	Other nondurables	5%

Notes: Table shows the reallocation of spending from six merchant-level Plaid categories into broader categories used in our analysis. Columns (1) and (2) show merchant-level revenue components and their share of total revenue. Columns (3) and (4) show mapped spending categories and their corresponding share of reallocated spending. For the first five categories in Panels A through E, we follow the methodology of Ganong and Noel (2019), who estimate product-type revenue shares from 10-K filings of leading merchants in each category. For the "other retail" category in Panel F, we base the allocation on the composition of US ecommerce revenue in 2020 Bledsoe (2024).

other retail (e.g., Amazon). For the first five categories, we follow Ganong and Noel (2019), who analyze 10-K filings from leading merchants in each category (e.g., CVS and Walgreens for drug stores, Macy's for department stores), calculate revenue by product type, and split each category across durable and nondurable spending categories. To categorize "other retail," we follow the composition of US ecommerce revenue in 2020 (Bledsoe, 2024). Appendix Table C.1 summarizes these reallocations.

To address the second and third limitations, we first map ambiguous Plaid categories to one of three "catch-all" categories: other retail, other payments, and other transfers. Then, we perform regular expression searches on transaction memos to pull transactions out of these catch-all categories and to recategorize misclassified transactions in other categories.

Beyond these limitations, our data face several common challenges inherent to bank account transactions datasets. Transactions are only observable and categorizable to the extent that they appear on linked bank account statements and have informative memos. Cash withdrawals and external transfers are observed in the data, but they mask underlying purchases and payments that we cannot observe. Mortgage and rent payments are not captured for many users due to being paid by check, peer-to-peer transfers, or other transactions with uninformative memos. The imperfect mapping between merchant and consumption categories discussed above is also a common feature of transactions data.

After applying the outflows categorization algorithm, we have the following categories:

- **Durables:** Auto parts & repair, home improvement, insurance, other durables
- **Nondurables:** Cash, digital entertainment, other entertainment, food services, gas stations, groceries, healthcare, personal care services, professional services, taxis, transportation, travel, utilities, other nondurables
- **Payments:** Auto loans, non-auto loans, buy now pay later, EarnIn earned wage access, other earned wage access, housing, overdraft & late fees, other payments
- **Internal transfers:** Transfers across bank accounts, transfers to investment accounts, credit card payments, other internal transfers
- **External transfers:** Checks, peer-to-peer transfers, other external transfers

C.2 Survey Outreach and Response

We send survey invitations to a restricted sample of EarnIn users who met minimum data quality thresholds based on their linked transactions data over the 12 months preceding each survey. Waves 2 and 3 imposed more stringent restrictions than wave 1. Additionally, wave 2 – fielded as a follow-up to wave 1 – applied consistency checks to users' wave 1 survey responses. The full sampling criteria for each wave's sampling frame are listed below.

- Wave 1 (September 2022)
  - Non-missing earnings data at least once between September 2021 and August 2022
  - Non-missing balances data in each bi-weekly period from September 2021 through August 2022
  - First recorded transaction before September 1, 2021 and latest recorded transaction after August 15, 2022

  - At least 5 outflows per month between September 2021 and August 2022
  - Non-missing bank connection date

- Wave 2 (July 2024; resampled Wave 1 users)
  - Completed the wave 1 survey
  - Still in the EarnIn database as of June 2024
  - Took at least 3.5 minutes to complete the wave 1 survey
  - Reported consistent debt amounts in the wave 1 survey (i.e., users who report zero debt must report N/A for debt manageability, and vice versa)
  - At least 20 outflows per month each month between June 2023 and May 2024
  - Non-missing balances data each week for at least 9 months between June 2023 and May 2024
  - Sufficient categorizable spending ($\frac{\text{Consumption}}{\text{Outflows - Internal Transfers}} \geq 20\%$) for at least 9 months between June 2023 and May 2024
  - Reasonable balance of inflows and outflows ($\frac{\text{Outflows}}{\text{Inflows}} \in [50\%, 150\%]$) for at least 9 months between June 2023 and May 2024
  - Less than 1% of transaction memos between June 2023 and May 2024 are uninformative (i.e., "CREDIT," "DEBIT," or missing)

- Wave 3 (November 2024; repeated cross-section)
  - Did not take the wave 1 survey
  - Non-missing earnings data at least once between October 2023 and September 2024
  - At least 20 outflows per month each month between October 2023 and September 2024
  - Non-missing balances data each week for at least 9 months between October 2023 and September 2024
  - Sufficient categorizable spending ($\frac{\text{Consumption}}{\text{Outflows - Internal Transfers}} \geq 20\%$) for at least 9 months between October 2023 and September 2024
  - Reasonable balance of inflows and outflows ($\frac{\text{Outflows}}{\text{Inflows}} \in [50\%, 150\%]$) for at least 9 months between October 2023 and September 2024
  - Less than 1% of transaction memos between October 2023 and September 2024 are uninformative (i.e., "CREDIT," "DEBIT," or missing)
  - Bank connection date non-missing and before September 1, 2021

Applying these sample restrictions, our sampling frames included 500,804 users for wave 1, 4,652 for wave 2, and 318,710 for wave 3. EarnIn further limited each sampling frame to users who had not yet reached its weekly cap for email marketing communications. This constraint did not affect the wave 1 sampling frame but reduced the wave 2 and 3 sampling frames to 3,900 and 218,615 users, respectively.

For wave 1, EarnIn sent invitations in waves and closed the survey after 250,000 were sent, at which point 10,103 respondents had completed the survey and our incentive budget was fully spent. For waves 2 and 3, EarnIn sent invitations to the full sampling frames and closed each survey after two reminder emails, resulting in 875 responses for wave 2 and 4,888 responses for wave 3. As a result, we received and aggregate response rate of 3.4% – 4% for wave 1, 22% for wave 2, and 2% for wave 3.

C.3 Sample Restrictions

We apply five sets of sample restrictions to the combined survey samples to arrive at our analysis sample.

- First, when merging survey respondents to the EarnIn database we drop respondents who deleted their EarnIn accounts or delinked their bank accounts. This reduces the number of users from 14,991 to 14,817.
- Second, we apply the survey data quality restrictions listed below. This reduces the number of users from 14,817 to 14,386.
  - Survey duration at least 3.5 minutes (approximately the 5^{th} percentile)
  - Reported debt amounts are consistent (i.e., users who report zero debt must report N/A for debt manageability, and vice versa)
- Third, we apply the transactions data quality restrictions listed below. These restrictions are designed to drop users who do not primarily consume through the bank accounts connected to EarnIn, which limits the extent to which we observe their consumption. We apply restrictions using the 12 months prior to each survey and up to 12 months after each survey (we observe 12 post-survey months for wave 1, 5 for wave 2, and 0 for wave 3). This reduces the number of users from 14,386 to 8,944.
  - Sufficient transaction activity: 20+ outflows per month for all months
  - Sufficient balances data: Non-missing balances each week for at least 75% of months
  - Sufficient categorizable spending: $\frac{\text{Consumption}}{\text{Outflows - Internal Transfers}} \geq 20\%$ for at least 75% of months
  - Reasonable balance of inflows and outflows: $\frac{\text{Outflows}}{\text{Inflows}} \in [50\%, 150\%]$ for at least 75% of months
  - Informative memos: $< 1\%$ of memos are "CREDIT", "DEBIT", or missing across months
- Fourth, we trim users with expectations outside of the percentiles listed below. We calculate percentile cutoffs separately for each survey wave. This reduces the number of users from 8,944 to 7,465.
  - $E_t G^Y_{t+1}$ (P3-P97)
  - $E_t \pi_{t+1}$ (P3-P97)
  - $E_t \pi_{t+3}$ (P3-P97)
  - $E_t R^S_{t+1}$ (P1-P97)
  - $E_t R^D_{t+1}$ (P1-P97)
- Fifth, we trim the variables listed below. Before trimming, we restrict to the 12-month pre-survey period, deflate to September 2022 prices, and collapse all variables to the annual level. We calculate percentile cutoffs separately for each survey wave. This reduces the number of users from 7,465 to 5,962.
  - Expected levered return ($E_t \ln R_{t+1}$) (P3-P97)
  - Nondurables spending (n_t) (P1-P99)

– Income (Y_t) (P1-P99)
– APC ($\tilde{c}_t$) (P2.5-P97.5)
– Wealth-to-income ($\frac{A_t R_t}{Y_t}$) (P5-P95)

C.4 Variable Measurement

C.4.1 Consumption, Income, and APCs

Consumption: In the data we measure spending, not consumption. We approximate consumption by scaling observed nondurables spending (from the EarnIn transactions data) by our assumed nondurables share of spending (α). To measure nondurables spending, we aggregate outflows categorized as nondurables over the 12 months prior to the survey.

Income (Y_t): We measure income as the sum of categorized post-tax labor earnings and unemployment benefits from the EarnIn transactions data, aggregated over the 12 months prior to the survey.

APCs ($\frac{C_t}{Y_t}$): We take the ratio of consumption to income.

C.4.2 Wealth-to-Income Ratio

Wealth ($A_t R_t$): In the survey, we ask respondents to report the dollar range of their liquid assets and debt.[18] Liquid assets are reported in the following bins: \$0 to \$499, \$500 to \$999, \$1,000 to \$2,499, \$2,500 to \$4,999, \$5,000 to \$9,999, \$10,000 to \$24,999, and \$25,000 or more. Total debt is reported in the following bins: \$0, \$1 to \$999, \$1,000 to \$4,999, \$5,000 to \$9,999, \$10,000 to \$24,999, \$25,000 to \$49,999, and \$50,000 or more. Because these variables are censored and do not capture illiquid assets, we impute total assets and total debt with an XGBoost model, as outlined in Appendix D.1.

Wealth-to-Income Ratio $\frac{A_t R_t}{Y_t}$: We take the ratio of wealth (imputed total assets minus imputed total debt) to income.

C.4.3 Beliefs

We measure beliefs in each survey wave. Note that beliefs enter the dynamic frictionless APC formula in *gross* terms (e.g., 5% expected inflation enters as 1.05).

Income Growth Expectations ($E_t \ln G^Y_{t+k}$): We elicit income growth expectations for $j = 1$ in the survey. We impute income growth expectations for $j > 1$ using the imputation procedure described in Appendix D.2.3.

Inflation Expectations ($E_t \ln \pi_{t+k}$): We elicit inflation expectations for $j = 1, 3$ in the survey. We impute inflation expectations for $j = 2$ and $j \geq 4$ using the imputation procedure described in Appendix D.2.1.

[18] In the survey, we define liquid assets as "money in a checking account, a savings account, a money market account, or somewhere else." We define debt as "all of your household's current debts, including mortgages, bank loans, student loans, money owed to people, medical debt, past-due bills, and credit card balances that are carried over from prior months."

Interest Rate Expectations ($E_t \ln R_{t+k}$): We assume individuals form interest rate expectations for each component of net worth: liquid assets or "savings" ($E_t R^S$), illiquid assets ($E_t R^I$), and debt ($E_t R^D$). For the wedge calculation, we focus on the expected *levered* interest rate, $E_t R$, which reflects the expected return on a marginal dollar of net worth. This measure can be expressed as a weighted average of the expected interest rates for each component of net worth, with the weights corresponding to each component's share of net worth.

In the survey, we elicit expected interest rates on liquid assets and debt for $j = 1$, but not for illiquid assets. To compute the expected levered interest rate, we take the weighted average of expected rates on liquid assets and debt, using weights based on *liquid* net worth (i.e., liquid assets minus debt). This approach implicitly assumes that the expected return on illiquid assets can be approximated by a weighted average of the expected returns on liquid assets and debt. We impute the term structure of levered interest rate expectations using the imputation procedure described in Section Appendix D.2.2.

C.4.4 Marginal Propensity to Consume

Observed MPC We measure individual-level MPCs based on consumers' non-durable spending responses to the March 2021 stimulus payments. These checks provided \$1,400 to each eligible individual, with an additional \$1,400 for each dependent.[19] Approximately 68% of the survey analysis sample received a stimulus check. We determine each user's stimulus payment date and amount from the transactions data. For each user, we examine consumption from 28 days before to 27 days after the stimulus check was received. Days -27 through -1 are the "pre" period, and days 0 through 27 are the "post" period. We then use the same date ranges in 2022 and 2023 as comparison periods. We calculate each individual's MPC as follows:

$$MPC_i = \frac{1}{StimulusAmount_i} \times (\Delta Spend_i^{2021} - \frac{\Delta Spend_i^{2022} + \Delta Spend_i^{2023}}{2}) \tag{9}$$

where

$$\Delta Spend_i^t = Spend_i^{Post,t} - Spend_i^{Pre,t} \tag{10}$$

Our MPC measure captures the "excess" consumption associated with receipt of the stimulus check. We note that this measure should be interpreted as at best a proxy for an individual's MPC, as we only have three observations per person. As such, this measure is unlikely an asymptotically valid estimate of the individual's true MPC. The median estimated MPC is 30%. There are a few extreme outliers (e.g., below -500% or above 500%), likely due to large, one-time purchases. Given this feature of the data, we winsorize MPCs at the 5th and 95th percentiles.

Hypothetical MPC

C.4.5 Financial Distress

D Imputations

D.1 Wealth

In the survey, we ask respondents to report the dollar range of their liquid assets and debt. Because these variables are censored and do not capture illiquid assets, we impute total assets and total

[19] The stimulus payment dates range from March 12, 2021 to May 28, 2021.

debt with an XGBoost model. XGBoost is a supervised learning algorithm that sequentially builds an ensemble of decision trees, using gradient boosting to improve each new tree. We use data from the 2016, 2019, and 2022 waves of the Survey of Consumer Finances (SCF). Following Kaplan and Violante (2014), when processing the SCF data we exclude the top 5% of the income distribution and exclude individuals below age 18 or above age 79. The predictor variables in our model include the surveyed liquid asset and debt bins along with other variables that are measured in all three survey waves and can be replicated the SCF (income range, has mortgage, has auto loan, has credit card debt, has student debt, age, gender, marital status, number of children, race, and education).

D.2 Term Structure of Beliefs

To calculate dynamic wedges, we need subjective beliefs over an infinite horizon. We measure the following subjective beliefs:

- Expected inflation $\widetilde{E}_{i,t}\pi_{t+k}$ for periods $k = 1, 3$ (survey waves 1, 2, and 3)
- Expected income growth $\widetilde{E}_{i,t}G^{Y}_{i,t+k}$ for period $k = 1$ (survey waves 1, 2, and 3)
- Expected interest rate on liquid assets $\widetilde{E}_{i,t}R^{S}_{i,t+k}$ for period $k = 1$ (survey waves 1, 2, and 3)
- Expected interest rate on debt $\widetilde{E}_{i,t}R^{D}_{i,t+k}$ for period $k = 1$ (survey waves 1, 2, and 3)
- Expected spending growth $\widetilde{E}_{i,t}G^{C}_{i,t+k}$ for period $k = 1$ (survey waves 2 and 3 only)

Our dynamic wedge specification allows a variable term structure of beliefs over an infinite horizon. Because we don't observe the full term structure, we must impute the unobserved portion. Our imputation approach is outlined below.

D.2.1 Inflation Expectations

We assume that users' inflation expectations for k years ahead, $\widetilde{E}_{i,t}\pi_{t+k}$, consist of a sophisticated component and a persistent, user-specific bias. This bias reflects long-run deviations from sophisticated expectations and is heterogeneous across individuals.

We start by calibrating the term structure of sophisticated inflation expectations, denoted $\widetilde{E}_{s,t}\pi_{t+k}$. We use the Federal Reserve Bank of Cleveland's term structure model, which calculates inflation expectations for time $t + k$ for $k = 1, ..., 30$. This model synthesizes data on inflation, Treasury yields, inflation swaps, and survey-based expectations to represent the beliefs of sophisticated investors. The model is updated each month, providing a separate term structure for each survey wave.

Next, we estimate each user's persistent expectations bias by taking the ratio of their observed expectations at $t + 1$ and $t + 3$ relative to the corresponding sophisticated expectations.

$$Bias = 0.5 \left(\frac{\widetilde{E}_{i,t}\pi_{t+1}}{\widetilde{E}_{s,t}\pi_{t+1}} + \frac{\widetilde{E}_{i,t}\pi_{t+3}}{\widetilde{E}_{s,t}\pi_{t+3}} \right)$$

We impute missing expectations using the following approach:

- For $t+2$, we set expectations as the average of the user's observed $t+1$ and $t+3$ expectations.

$$\widetilde{E}_{i,t}\pi_{t+k} = 0.5\left(\widetilde{E}_{i,t}\pi_{t+1} + \widetilde{E}_{i,t}\pi_{t+3}\right) \quad \text{for } k = 2$$

- For $t+4$ through $t+30$, we assume expectations equal the sophisticated benchmark scaled by the individual's persistent bias ratio.

$$\widetilde{E}_{i,t}\pi_{t+k} = Bias * \widetilde{E}_{s,t}\pi_{t+k} \quad \text{for } k \in [4, 30]$$

- For horizons beyond $t+30$, where the sophisticated benchmark is unavailable, expectations are held constant at the $t+30$ level.

$$\widetilde{E}_{i,t}\pi_{t+k} = Bias * \widetilde{E}_{s,t}\pi_{t+30} \quad \text{for } k > 30$$

D.2.2 Interest Rate Expectations

Imputing the term structure of levered interest rate expectations requires imputing the term structures of its four components: (1) liquid assets, (2) total debt, (3) the expected interest rate on liquid assets, and (4) the expected interest rate on debt. While there exist household surveys that elicit $t+1$ interest rate expectations, there is little empirical evidence to guide assumptions about long-run interest rate expectations. Further, given the financial constraints facing the EarnIn sample, we are hesitant to make assumptions about long-run portfolio shares. As a result, we assume that levered interest rate expectations remain constant over the horizon.

D.2.3 Income Growth Expectations

We accommodate short-run variation in expected income growth–such as anticipated job switches or job loss–while ensuring that expectations eventually stabilize toward a long-run lifecycle profile.

We start by calibrating a smoothed lifecycle profile of income growth, denoted by $LC(t+k)$. This lifecycle term structure reflects how expectations typically vary with age and is estimated using Michigan Survey of Consumers data from September 2021 through April 2025. We calculate the median expected income growth by age group (18-24, 25-29, 30-34, ..., 65-69, 70-74, 75 and older), then smooth across age bins by interpolating between age bin medians.

We impute users' $t+2$ expectations from their $t+1$ expectations to account for short-run deviations in expected income growth. In lieu of publicly available survey data that measures both $t+1$ and $t+2$ income growth expectations, we leverage the panel structure of the Survey of Consumer Expectations (SCE) to fit this imputation model. The SCE surveys households about their $t+1$ expectations each month for up to 12 months. We fit a quadratic regression of respondents' month-12 expectations on their month-1 expectations, with the estimated coefficients denoted by $\hat{\beta}$. This imputation assumes that $t+1$ expectations in month 12 are informative of $t+2$ expectations in month 1 (approximately one year earlier).

We impute missing expectations using the following approach:

- For $t+2$, we impute expectations from observed $t+1$ expectations using the quadratic regression fitted on SCE data.

$$\widetilde{E}_{i,t}G^Y_{i,t+k} = \hat{\beta}_0 + \hat{\beta}_1\widetilde{E}_{i,t}G^Y_{i,t+1} + \hat{\beta}_2(\widetilde{E}_{i,t}G^Y_{i,t+1})^2 \quad \text{for } k = 2$$

- For $t+3$ through $t+30$, we immediately converge user's expectations to the lifecycle term structure, adjusted to start from the respondent's age in the survey. If the user's age is missing, we start the term structure from the median respondent age of 36.

$$\widetilde{E}_{i,t}G^{Y}_{i,t+k} = LC_{a(i),t+k} \quad \text{for } k \in [3,30]$$

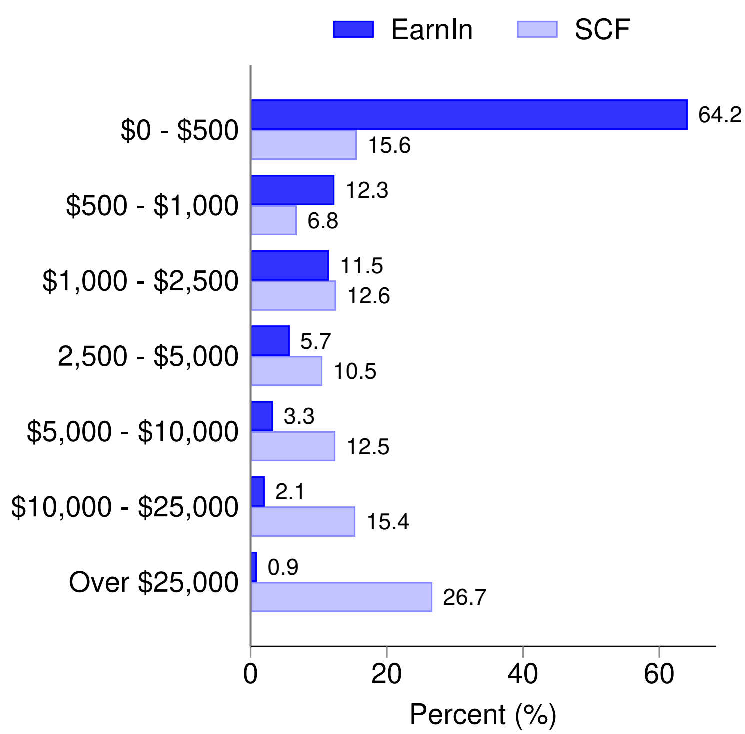
- For horizons beyond $t+30$, expectations are held constant at the $t+30$ level.

$$\widetilde{E}_{i,t}G^{Y}_{i,t+k} = LC_{a(i),t+30} \quad \text{for } k > 30$$

E Representativeness of the EarnIn Sample

E.1 Wealth Distribution

Figure E.1. Distribution of Liquid Wealth in EarnIn versus the SCF



Notes: Figure presents a bar graph showing the distribution of liquid assets among EarnIn survey respondents compared to respondents in the 2022 Survey of Consumer Finances. Following Kaplan and Violante (2014), we define liquid assets as the sum of assets held in transactions accounts. Includes users from all three survey waves that meet the restrictions outlined in Appendix C.

E.2 Income Distribution

We assign each user to a percentile of the income distribution among employed US individuals. Because we do not observe gross household income in the EarnIn transactions data and our survey measure is imprecise, we base this calculation on users' post-tax labor earnings from the EarnIn data. We assign percentiles using person-level data from the Current Population Survey Annual Social and Economic Supplement (United States Census Bureau, 2025). While the CPS ASEC does not measure post-tax labor earnings, we can approximate this measure using the CPS ASEC Tax Model, which estimates an individual's federal and state tax liabilities (Lin, 2022). To our knowledge, no other US household survey measures or estimates post-tax income or tax liabilities.

The CPS asks respondents about their sources of income, household structure, and state of residence. The CPS ASEC Tax Model uses these inputs to impute adjusted gross income, taxable income, payroll taxes, and federal and state tax liabilities (before and after refundable credits). However, public CPS ASEC data does not separate estimated tax liabilities by the associated source of income, so it does not offer a precise measure of post-tax labor earnings. We estimate post-tax labor earnings in the CPS as follows:

$$Earnings^{Post} = Earnings^{Pre} - PayrollTax - \frac{Earnings^{Pre}}{TotalIncome^{Pre}} (FedTax + StateTax) \qquad (11)$$

The term $TotalIncome^{Pre}$ reflects the sum of taxable income components. These components include wage and salary earnings, self-employment earnings, interest income, dividends, alimony, rent income, unemployment benefits, Social Security income, Veteran's Administration income, capital gains, rents or royalties, estate or trust income, pensions, annuities, most survivor income, and most disability income. The key assumption in this calculation is that the share of tax liabilities driven by labor earnings equals the share of taxable income (before refundable credits) from labor earnings.

In the CPS ASEC sample, we restrict to individuals who (i) are age 18 or older, (ii) are classified as adults, and (iii) received wage or salary earnings during the reference years. These restrictions allow us to estimate the distribution of annual labor earnings for US adults. When calculating percentiles, we incorporate probability weights provided in the CPS ASEC data.

E.3 Subjective Expectations

Table E.1 presents forecast errors in expected inflation, nominal income growth, and interest rates for wave 1 users, for whom we observe 12 months of post-survey data and can compare expectations to realized outcomes.[20] To calculate income growth forecast errors, we take the difference between users' expectations and their realized income growth in the EarnIn transactions data. For inflation and interest rate forecast errors, we compare users' expectations to aggregate outcomes, because individualized inflation rates and interests rates reflecting each person's distinct consumption basket and asset mix are unobserved. Specifically, we use annual CPI growth from BLS, the national average deposit rate on savings from the FDIC, and the average credit card interest rate from the Board of Governors of the Federal Reserve System.[21]

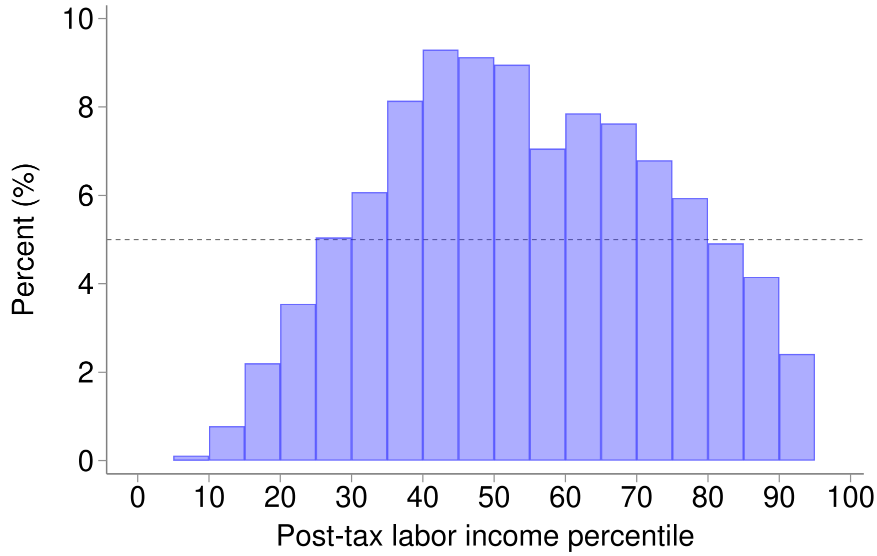
Realized inflation between October 2022 and October 2023 was 3.7 percent – 5.4 percentage points lower than the average forecast of 9.1 percent. This forecast error aligns with respondents' 2.7 percentage-point overestimation of realized inflation in the prior year, which could reflect higher exposure to inflation among our sample. Respondents also overestimated the national deposit rate (0.45%) by 3.0 percentage points and underestimated the average credit card interest rate (21.3%) by 7.1 percentage points. Notably, respondents' income growth expectations are remarkably accurate on average. The average wave 1 respondent experiences 20.4% nominal post-tax income growth in the 12 months after the survey. While the average forecast error is -14.8 percentage points, the median is just -3.6 percentage points.

[20] The EarnIn administrative dataset ends in November 2024. As a result, we observe 12 months of post-survey data for wave 1, 4 months for wave 2, and zero months for wave 3.

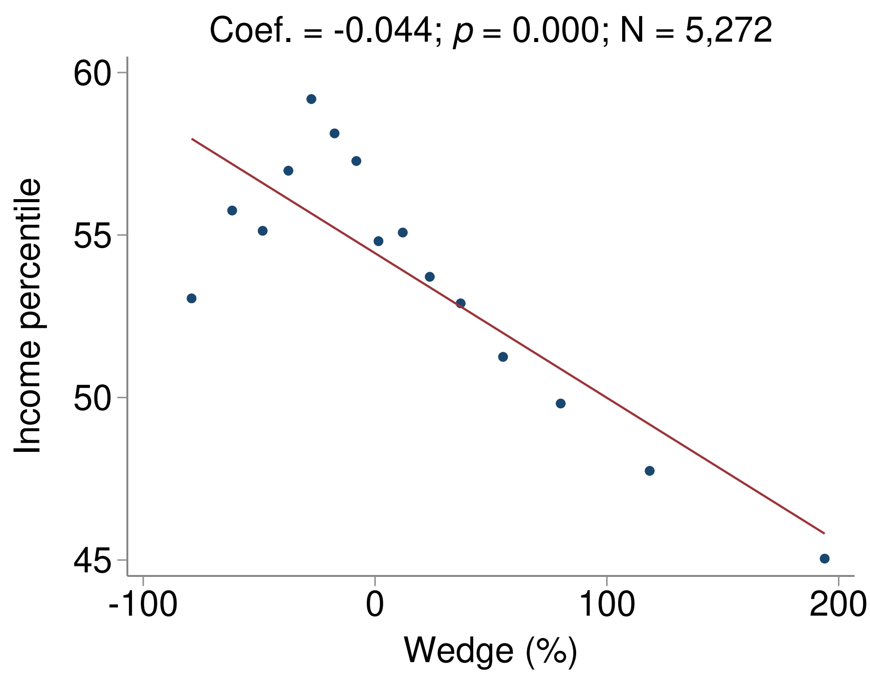
[21] We use CPI growth as of October 2022 for perceived inflation and October 2023 for realized inflation. The national deposit rate on savings is as of September 2023. For the credit card interest rate, we take the average across August and November 2023, as the data are published quarterly.

Figure E.2. Post-Tax Labor Income Percentiles

Panel A. Distribution of Income Percentiles



Panel B. Correlation with Consumption Wedges



Notes: Panel A presents the distribution of post-tax labor income percentiles among our EarnIn analysis sample, estimated using CPS ASEC data and the CPS ASEC Tax Model. Panel B presents a binned scatterplot between dynamic consumption wedges and users' income percentiles. CPS ASEC sample restricts to adults age 18 or older who received wage or salary earnings during the reference year. Black dashed lines represent the uniform distribution. Wedges are trimmed at the 1st and 95th percentiles.

Table E.1. Distribution of Economic Expectations

	Ex-Post	Distribution							
		Mean	SD	P10	P25	P50	P75	P90	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Expectations									
E(Inflation) 2022-23		9.1	9.6	2.0	5.0	7.0	10.0	20.0	4,354
E(Inflation) 2024-25		5.1	12.1	-7.0	-2.0	5.0	10.0	20.0	4,339
Perceived inflation 2021-22		10.9	12.6	2.0	5.0	8.0	13.0	25.0	4,334
E(Income growth)		5.5	10.0	-3.0	2.0	4.2	10.0	15.0	4,354
E(Real income growth)		-3.6	13.6	-20.0	-8.0	-3.0	2.0	10.0	4,354
E(Interest on savings)		3.5	4.0	0.2	1.0	2.0	5.0	10.0	4,354
E(Interest on borrowing)		14.3	10.0	3.0	5.0	12.0	20.0	28.0	4,354
Panel B: Deviations from ex-post realizations									
Inflation 2022-23	3.7	5.4	9.6	-1.7	1.3	3.3	6.3	16.3	4,354
Inflation 2021-22	8.2	2.7	12.6	-6.2	-3.2	-0.2	4.8	16.8	4,334
Income growth	20.4	-14.8	47.9	-83.4	-24.8	-3.6	10.6	28.4	4,349
Real income growth	16.7	-20.3	47.0	-87.4	-32.3	-9.5	5.6	23.1	4,349
Interest on savings	0.5	3.0	4.0	-0.2	0.6	1.5	4.6	9.6	4,354
Interest on borrowing	21.3	-7.1	10.0	-18.3	-16.3	-9.3	-1.3	6.7	4,354

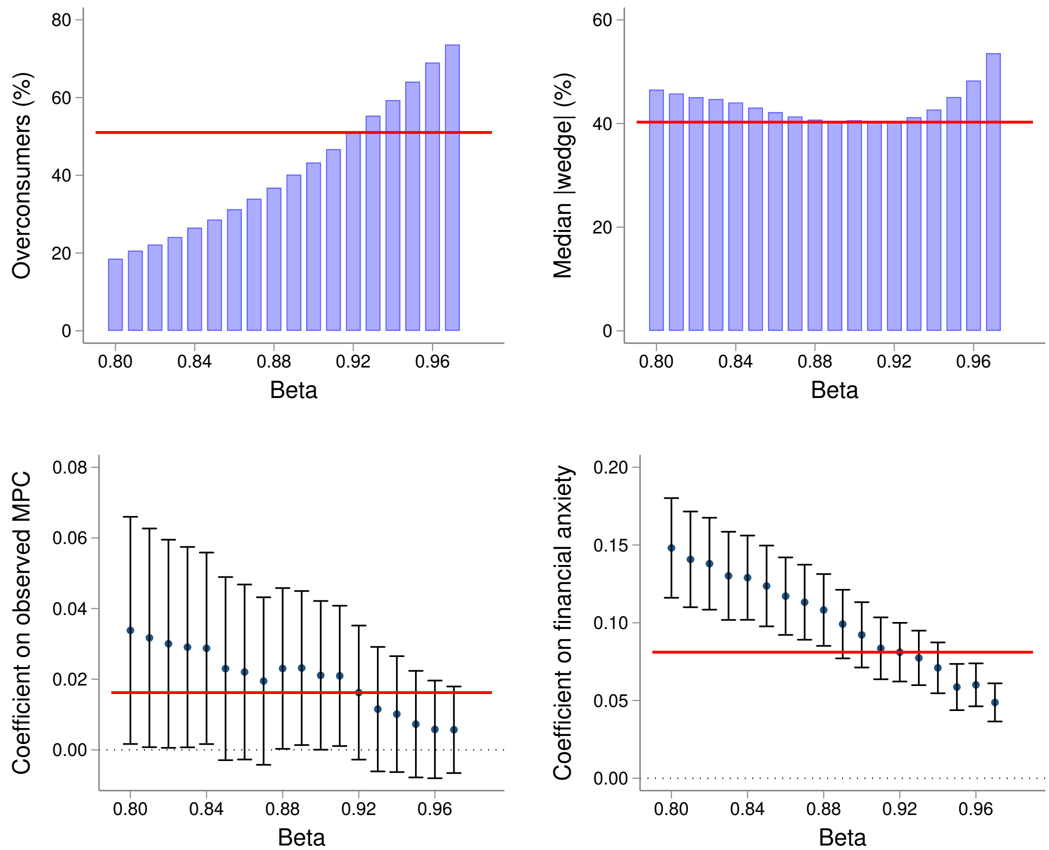
Notes: The table shows summary statistics for the economic expectations questions (Panel A) and the difference between expectations and realized values (Panel B). Includes wave 1 respondents within our analysis sample. Column (1) reflects the realized value of each economic variable. For both nominal and real income growth, deviations are measured against each user's realized annual income growth 12 months after the survey, based on the transactions data, and the ex-post value reflects the average earnings growth across users. For the remaining variables, deviations are measured against aggregate economic statistics.

F Robustness

F.1 Sensitivity Analysis

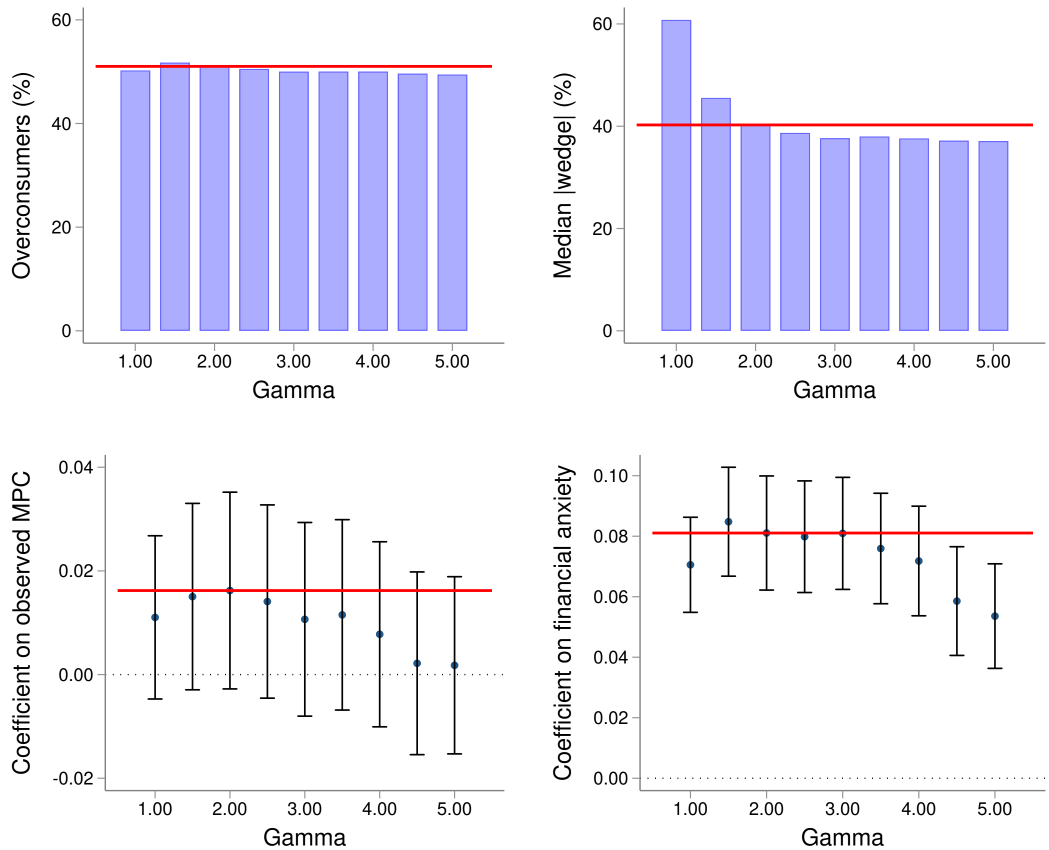
We test the robustness of the consumption wedge to our assumed parameters and data choices. For this analysis, we focus on the sensitivity of the share of users with a positive wedge (i.e., over-consumers), the median wedge in absolute value terms, and the correlations with nondurable MPCs and the indicator for high financial anxiety.

Figure F.1. Sensitivity of Dynamic Wedges to Beta



Notes: The figure presents the sensitivity of four estimated results to our assumed value of beta in the dynamic wedge calculation, with the assumed value ranging from 0.80 to 0.98 in increments of 0.01 (our baseline calibration is 0.92). These results include the percent of users with a positive wedge (Panel A), the median absolute value wedge (Panel B), and the estimated coefficients from separate regressions of the observed nondurables MPC and the financial anxiety indicator on the consumption wedge (Panels C and D, respectively). We hold all other parameters constant at our baseline values. Wedges are trimmed at the 1st and 95th percentiles.

Figure F.2. Sensitivity of Dynamic Wedges to Gamma



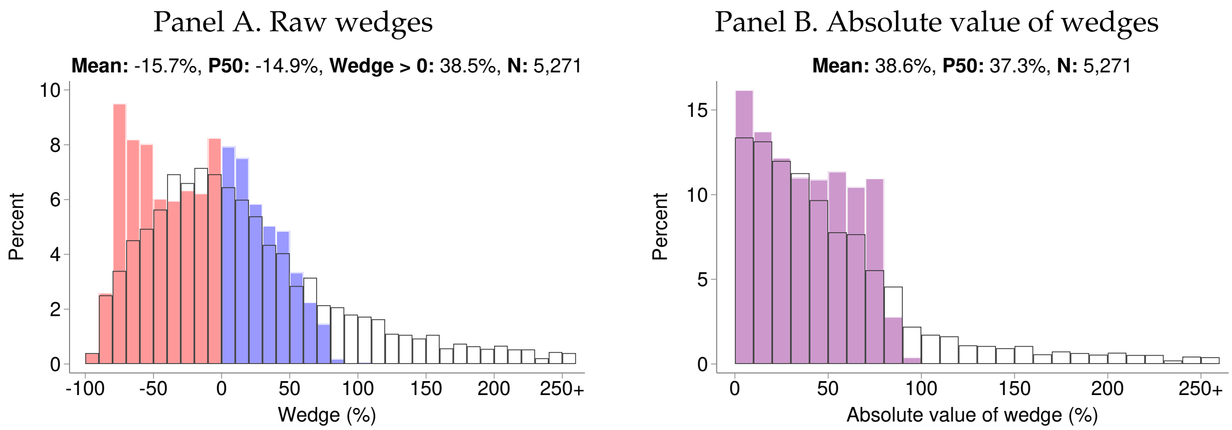
Notes: The figure presents the sensitivity of four estimated results to our assumed value of gamma in the dynamic wedge calculation, with the assumed value ranging from 1.0 to 5.0 in increments of 0.5 (our baseline calibration is 2.0). These results include the percent of users with a positive wedge (Panel A), the median absolute value wedge (Panel B), and the estimated coefficients from separate regressions of observed nondurables MPC and the financial anxiety indicator on the consumption wedge (Panels C and D, respectively). We hold all other parameters constant at our baseline values. Wedges are trimmed at the 1$^{\text{st}}$ and 95$^{\text{th}}$ percentiles.

Table F.1. Distribution of Wedge-Minimizing Preference Types

Preference type (1)	Preferences values (2)	Share of Aguiar et al. sample (3)	Share of EarnIn sample (4)
I	$\beta = 0.97, \gamma = 1.89$	44.7%	41.1%
II	$\beta = 0.94, \gamma = 1.05$	33.7%	32.2%
III	$\beta = 0.72, \gamma = 0.35$	21.6%	26.7%

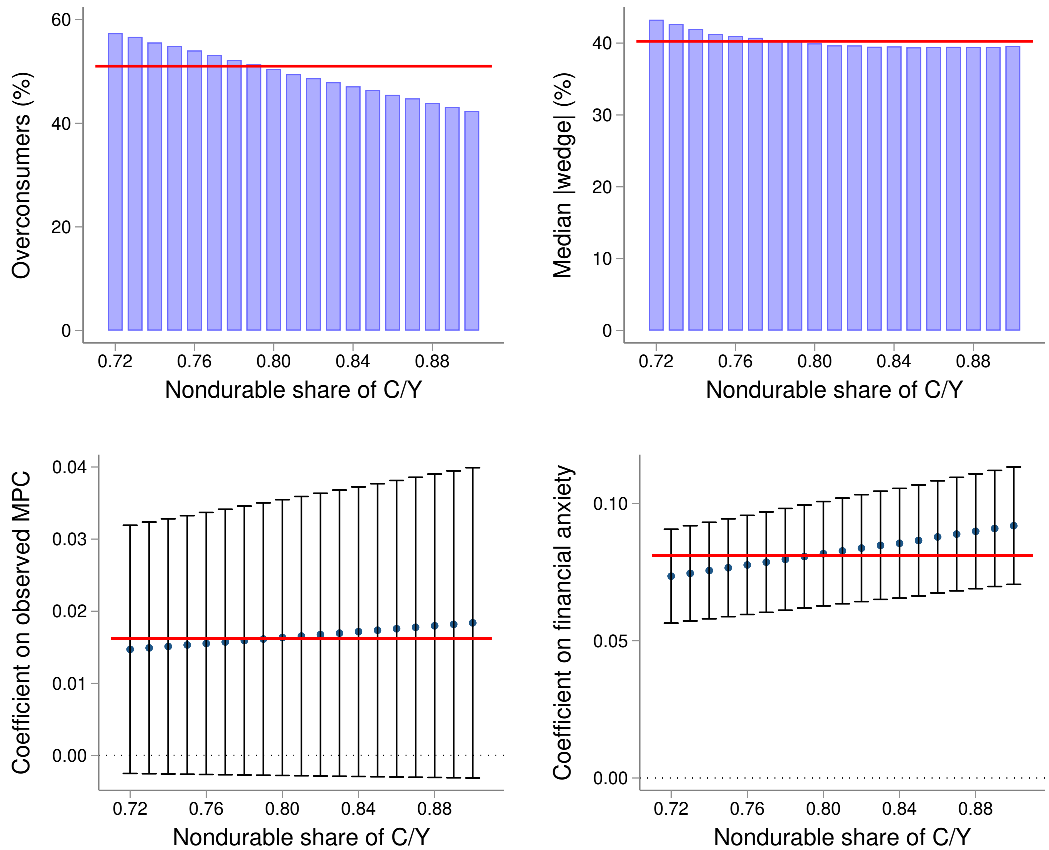
Notes: The table lists the three preference types outlined in Table 11 of Aguiar et al. (2024). Column (2) outlines the discount factor (β) and inverse IES (γ) for each preference type (for consistency, we report the inverse IES rather than the IES, σ, where $\gamma = 1/\sigma$). Column (3) presents the distribution of preference types among the sample in Table 11 of Aguiar et al. (2024). Column (4) presents the distribution of preference types among the EarnIn sample, where we assign preference types based on the type that minimizes the median absolute value of the wedge for each user.

Figure F.3. Distribution of Dynamic Consumption Wedges Using Wedge-Minimizing Preference Types



Notes: The figures show the distribution of dynamic consumption wedges (left) and their absolute values (right), assuming users have one of the three preference types outlined in Table 11 of Aguiar et al. (2024). We assign users to preference types based on which type minimizes the absolute value of their wedge (see Table F.1). Wedges are defined as the percent difference between the observed APC and frictionless APC, and they are trimmed at the 1^{st} and 95^{th} percentiles. The baseline distribution of dynamic wedges using homogeneous preferences (from Figure 2) is overlaid with hollow black bars.

Figure F.4. Sensitivity of Dynamic Wedges to Nondurables Share of Spending



Notes: The figure presents the sensitivity of four estimated results to our assumed nondurables share of spending in the dynamic wedge calculation, with the assumed value ranging from 72% to 90% in increments of 1 percentage point (our baseline calibration is 79.37%). These results include the percent of users with a positive wedge (Panel A), the median absolute value wedge (Panel B), and the estimated coefficients from separate regressions of the observed nondurables MPC and the financial anxiety indicator on the consumption wedge (Panels C and D, respectively). We hold all other parameters constant at our baseline values. Wedges are trimmed at the 1st and 95th percentiles.

Figure F.5. Sensitivity of Consumption Wedge to the Number of Months of Data

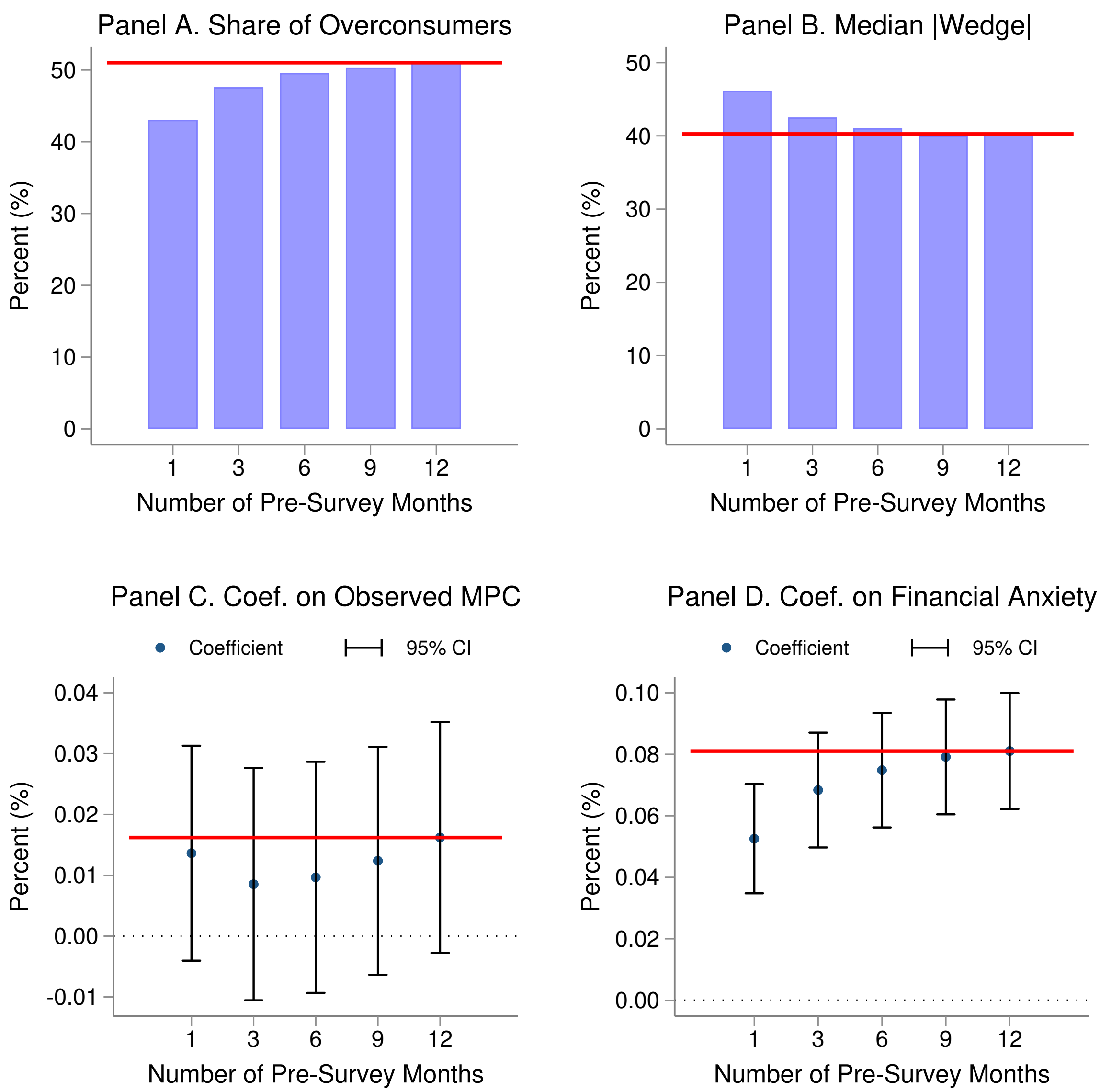
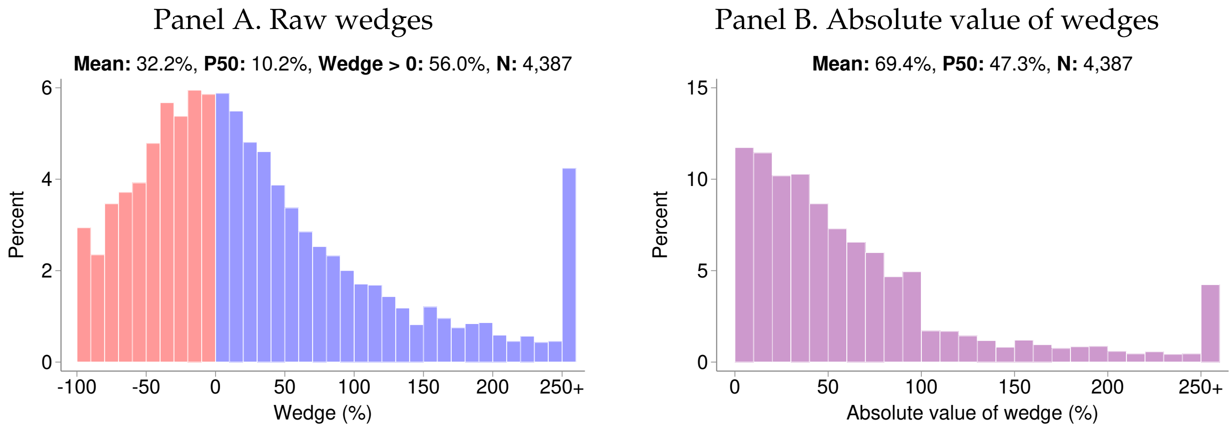


Figure presents the sensitivity of four estimated results to varying the number of months of pre-survey data. These results include the percent of users with a positive wedge (Panel A), the median absolute value wedge (Panel B), and the estimated coefficients from separate regressions of the observed nondurables MPC and the financial anxiety indicator on the consumption wedge (Panels C and D, respectively). Wedges are trimmed at the 1^{st} and 95^{th} percentiles. Our baseline specification uses 12 months of pre-survey data. When using less than 12 months of data, we annualize income when calculating the wealth-to-income ratio.

Figure F.6. Sensitivity of Consumption Wedge to a Constant Term Structure of Beliefs



The figures show the distribution of dynamic consumption wedges (left) and their absolute values (right), assuming users have a constant term structure of beliefs. Wedges are defined as the percent difference between the observed APC and frictionless APC, and they are trimmed at the 1st and 95th percentiles.

F.2 Measurement Error

Figure F.7. Sensitivity of Consumption Wedge to Dropping Users

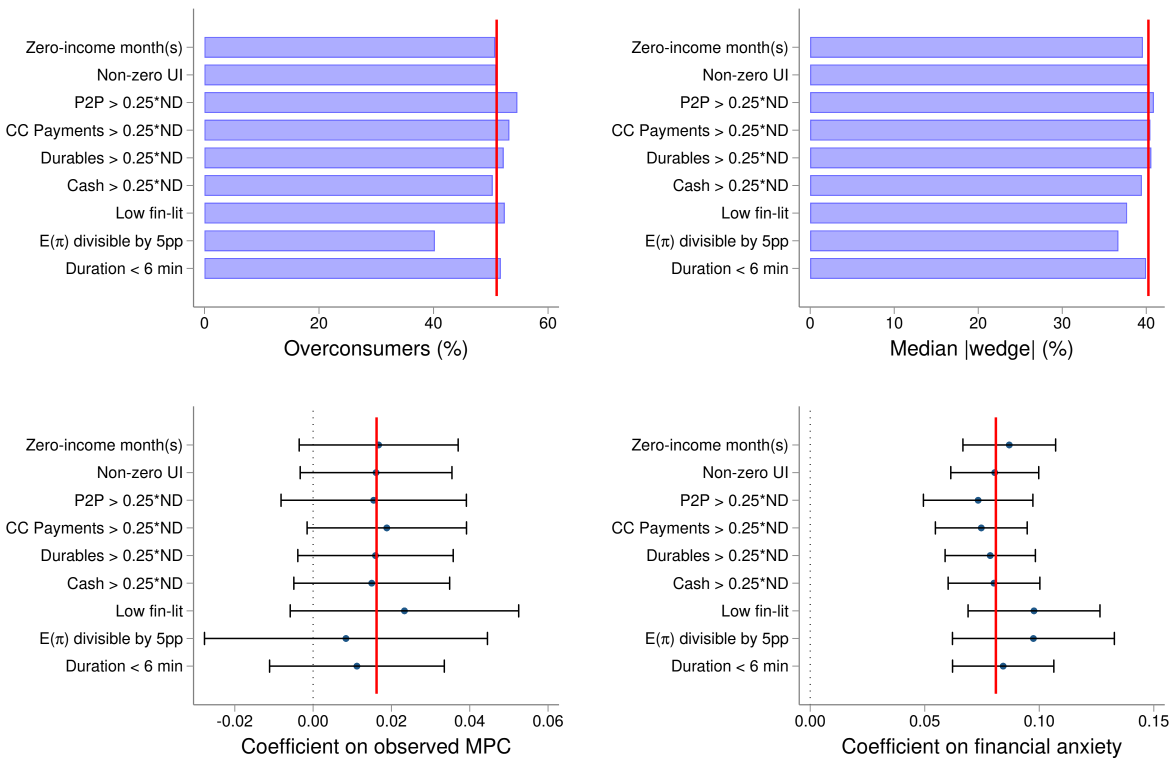


Figure presents the sensitivity of four estimated results to dropping users with plausibly high measurement error. These results include the percent of users with a positive wedge (Panel A), the median absolute value wedge (Panel B), and the estimated coefficients from separate regressions of the observed nondurables MPC and the financial anxiety indicator on the consumption wedge (Panels C and D, respectively). In the regressions, we cluster standard errors at the user level. For reference, our baseline results are shown in red. Wedges are trimmed at the 1^{st} and 95^{th} percentiles.

Figure F.8. Robustness of Consumption Wedges to Clustering Users

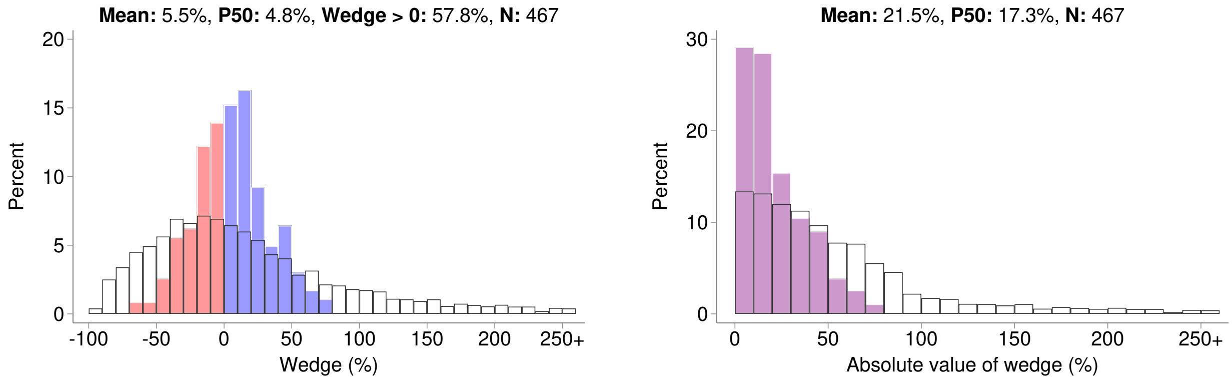


Figure presents the sensitivity of the wedge distribution to clustering users and taking the within-cluster median of each wedge input before calculating wedges. We use the *k*-prototypes clustering algorithm with 500 bins. Wedges are trimmed at the 1st and 95th percentiles. The baseline distribution of user-level dynamic wedges (from Figure 2) is overlaid with hollow black bars.