# BEHAVIORAL INEQUALITY: THE CONTRIBUTION OF DECISION-MAKING FRICTIONS TO INEQUALITY*

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**Abstract**

We provide the first systematic quantification of the financial impact of decision-making frictions—such as failing to claim government benefits, choosing dominated insurance plans, not saving for retirement, and not quitting smoking— and how they aggregate to affect overall inequality. To make frictions across many domains comparable, we develop a framework in which each friction is characterized by three parameters: the share of the population at risk, the share affected by the friction, and the average loss conditional on being affected. Applying this framework to a combination of existing literature and survey data, we have three main findings. First, the aggregate financial impact of these frictions is large: the estimated annual loss is 8.23% of annual income for the bottom quartile of the income distribution and 2.96% for the top quartile. For low-income individuals, these losses are similar to consumption expenditure on utilities, and eight times larger than the impact of a major EITC expansion. Second, the losses from these frictions are regressive: they are larger for low-income individuals, primarily because their prevalence is higher. An exception is savings frictions, which create disproportionately larger losses for high-income individuals. Finally, we incorporate these frictions into a life cycle model and find that removing them decreases inequality in lifetime consumption, with not quitting smoking, stock market non-participation, and not claiming government benefits playing the largest roles of the frictions currently incorporated.

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A large body of literature in economics has studied inequality in income and wealth, documenting its evolution (Piketty, 2014; Saez and Zucman, 2016; Smith et al., 2023; Gomez, 2023), analyzing its determinants (Cagetti and De Nardi, 2008; De Nardi and Fella, 2017; Fagereng et al., 2020; Hubmer et al., 2021), and evaluating policies that could reduce it (Cagetti and De Nardi, 2009; Guvenen et al., 2023). The vast majority of this work uses models with fully optimizing households. At the same time, a large literature in behavioral economics has documented the presence of decision-making frictions across a wide range of economic decisions (Beshears et al., 2018a; National Academies of Sciences, Engineering, and Medicine, 2023; Campbell and Ramadorai, 2026). For example, households fail to claim government benefits for which they are eligible (Bhargava and Manoli, 2015; Finkelstein and Notowidigdo, 2019), choose dominated health insurance plans (Bhargava et al., 2017; Liu and Sydnor, 2022), pay avoidable fees on credit cards and bank accounts (Stango and Zinman, 2009; Gathergood et al., 2021), forego favorable investment opportunities (Campbell, 2006; Choi et al., 2010), and do not engage in beneficial health behaviors (Gruber and Köszegi, 2001; Giné et al., 2010).

This paper provides the first systematic quantification of how decision-making frictions in different domains aggregate to affect various measures of inequality. Our approach proceeds in two steps. In the first step, we review the existing literature and combine it with original analysis of microdata to estimate the prevalence and financial impact of 19 frictions for three income groups: low (bottom 25%), middle (25%–75%), and high (top 25%). The frictions span education choices, savings, borrowing, insurance, benefit claiming, and health behaviors. In the second step, we build a life cycle model that incorporates these frictions and use it to quantify their implications for inequality in lifetime consumable income, consumption, and wealth. Our focus is on inequality across households in the bulk of the distribution—for whom these frictions are likely most relevant—rather than households in the very top.

The first part of the paper aims to measure the financial impact of key behavioral frictions. Building on existing literature and consulting a range of domain experts, we focus on the 19 frictions listed in Table 1. The table shows a good overlap with the frictions discussed in financial literacy syllabi in the saving and borrowing categories (though not in the health and benefit categories).[1] Still, the list is by no means exhaustive. Importantly, while not everyone will agree that each of these constitutes a behavioral friction as opposed to an optimizing decision subject to unmodeled costs, we think there is value in systematically quantifying the inequality effects of these decisions that have been studied extensively in the literature. To measure the impact, we develop a framework in which each friction is characterized by three parameters for each income group $j$: the share at risk, $S_j$, the friction prevalence, $F_j$, and the average loss in consumable income conditional on being affected, $L_j$. We then estimate these parameters using a combination of prior literature and survey data such as the SCF, the PSID, and the NHIS. The product $S_j \cdot F_j \cdot L_j$ provides a summary measure of the average annual per-person impact of each friction on each income group, which we use to compare losses across frictions.

We find that decision-making frictions disproportionately affect lower-income individuals, both in prevalence and as a share of income, as reported in Table 3. Aggregating across the frictions, we estimate that the loss as

[1] Table A1 reports the frictions most commonly featured in syllabi which we do not cover.

Table 1: List of Decision-Making Frictions

| No. | Category | Friction | No. of Syllabi Covering Friction | |
|---|---|---|---|---|
| | | | Top Universities (Out of 10) | High Schools (Out of 10) |
| 1 | Education | Not Attending College Due to Frictions | 0 | 10 |
| 2 | Education | Attending 2-Year For-Profit Colleges | 0 | 1 |
| 3 | Savings | Not Meeting the Employer 401(k) Match | 3 | 3 |
| 4 | Savings | Not Investing in Stock Mutual Funds | 10 | 10 |
| 5 | Savings | Saving in Low Interest Accounts | 5 | 4 |
| 6 | Savings | Investing in Individual Stocks | 6 | 7 |
| 7 | Savings | Investing in High-Fee Mutual Funds | 4 | 1 |
| 8 | Borrowing | Not Refinancing a Mortgage | 6 | 2 |
| 9 | Borrowing | Not Getting an Additional Mortgage Quote | 1 | 0 |
| 10 | Borrowing | Suboptimally Repaying Credit Card Debt | 0 | 0 |
| 11 | Borrowing | Paying Late Fees | 2 | 8 |
| 12 | Borrowing | Paying Overdraft Fees | 4 | 6 |
| 13 | Insurance | Choosing Dominated Health Insurance | 0 | 2 |
| 14 | Insurance | Suboptimally Lapsing Life Insurance | 1 | 0 |
| 15 | Benefits | Not Claiming EITC Benefits | 1 | 1 |
| 16 | Benefits | Not Claiming SNAP Benefits | 0 | 0 |
| 17 | Health | Not Taking Statin Medications | 0 | 0 |
| 18 | Health | Not Screening for Colon Cancer | 0 | 0 |
| 19 | Health | Failing to Quit Smoking | 0 | 0 |

a percentage of annual income is approximately 8.23% for the low-income group, 4.98% for the middle-income group, and 2.96% for the high-income group. The frictions with the largest impact on low-income households as a share of income include overdraft fees, attending 2-year for-profit colleges, not refinancing mortgages, and failing to quit smoking. For high-income households, the largest frictions are excessive mutual fund fees and under-diversification. To put these magnitudes in perspective, the total loss for the low-income group is approximately 8.5 times larger than the effect of all states implementing a 25% EITC supplement, which would be a major expansion of one of the largest anti-poverty programs. This suggests that the cumulative impact of behavioral frictions on lower-income households is quantitatively large relative to the policy instruments typically studied in the context of inequality.

An important benefit of this empirical approach is that it does not require assumptions about (i) the correlation of different frictions within-individual, (ii) the autocorrelation of a given friction within-individual, or (iii) individuals' sophistication about the prevalence of frictions. In the second part of the paper, we complement this analysis using a structural life cycle model. While this approach requires us to take a stand on these three dimensions and inherently involves more assumptions, it allows us to model some of the frictions directly, quantify the dynamic effects of each friction accumulated over lifetimes, and—by endogenizing consumption-savings decisions—study effects on consumption and wealth inequality.

The life cycle model that we build captures institutionally realistic features of the choice environment faced by

US households in the 2010s, including income and employment risk, tax-advantaged retirement savings accounts, portfolio choice, unsecured debt, and a tax and social insurance system. We incorporate the subset of frictions currently included in the model for a share $F_j$ of households using our estimates from the first part of the paper and model frictions in one of two categories. The first category comprises frictions that affect decisions modeled explicitly, such as education or portfolio choice. In this case, turning on the friction corresponds to directly changing households' endogenous choices. The second category comprises frictions that affect decisions not modeled explicitly, such as payment of fees, smoking, or preventative healthcare. For these frictions, we calibrate the effect on model variables—such as income, transfers, or mortality—using our estimates from the first part of the paper.

Our main counterfactuals consist of turning off each friction individually, holding all other frictions at their baseline prevalence. We study the effects on lifetime consumable income, consumption, and wealth by income group, as reported in Table 6. The frictions with the largest effects on lifetime consumption are stock market non-participation and smoking. In terms of inequality across income groups, most frictions generate larger percentage losses in lifetime consumption for lower-income households. For example, removing the for-profit college friction raises lifetime consumption by approximately 0.433% for the low-income group relative to 0.025% for the high-income group, while removing the smoking friction raises lifetime consumption by approximately 3.225% for the low-income group relative to 0.467% for the high-income group. The frictions that are modeled as direct dollar losses—such as dominated insurance and fees—also generate larger percent effects for lower-income households, consistent with the empirical evidence on their prevalence across the income distribution. The main exception is the high-fee mutual fund friction, whose effect on lifetime consumption rises from 0.411% for the low-income group to 1.315% for the high-income group.

We also present results for population-wide measures of inequality in Table 7, examining changes in distributional statistics such as Gini coefficients (for lifetime consumable income and consumption) and percentile spreads (for wealth). We view the results by income group as more reliable, given that total inequality measures are sensitive to within-group heterogeneity in friction exposure, which we do not richly model. Nevertheless, removing frictions generally reduces inequality in lifetime consumable income and consumption, consistent with the fact that frictions disproportionately affect lower-income households. The friction with the largest effect on lifetime consumable-income and consumption inequality is smoking. Removing frictions also tends to compress the wealth distribution relative to the median. Stock market participation has the largest effect using each scenario's own survivor pool, while smoking is also important when we hold the survivor sample fixed. High-fee mutual funds are an exception to the general inequality pattern: removing this friction increases consumable-income and consumption inequality because the gains are largest for high-income households.

In future work, we plan examine the robustness of our findings to correlation in the prevalence of different frictions, the persistence of frictions within a given individual, individuals' sophistication about the likelihood of being subject to future frictions, and the extent to which individuals unaffected by a friction benefit indirectly through lower equilibrium prices from those who are (Gabaix and Laibson, 2006).

**Related Literature.** This paper is related to several strands of the literature. First, we contribute to the literature studying inequality in income and wealth, which has not typically focused on decision-making frictions. Our contribution is to provide a comprehensive accounting of the role that a large set of frictions play.[2]

Second, we contribute to the literature on behavioral household finance (see Beshears et al. 2018a, Gomes et al. 2021, and Campbell and Ramadorai 2026 for reviews). While this literature has studied individual frictions in a wide range of financial decisions, it has not attempted to quantify how these frictions aggregate across domains or to assess their implications for inequality, which is our contribution. It is important to recognize that our approach has two important limitations. First, we model all frictions in reduced form, remaining agnostic about possible microfoundations such as present bias, inattention, or limited cognition.[3] This approach allows us to build a tractable model that contains all of the frictions jointly, but limits our ability to draw conclusions about welfare or the effectiveness of specific policy interventions. Second, we evaluate the impact of frictions in partial equilibrium, given that building a general equilibrium model of all of these frictions is obviously intractable. Nevertheless, we view our results as providing a natural starting point for assessing the importance of decision-making frictions.

Third, our paper relates to similar efforts to aggregate across research findings. Like the MVPF calculations in Hendren and Sprung-Keyser (2020) and biases elicitations in Stango and Zinman (2023), we aim to find a common metric for outcomes across many different domains. Two important differences are that we do not rely on revealed preference and, because our goal is to quantify the impact of frictions rather than specific policies, we do not measure the cost to the government. By aggregating evidence from many studies, our work is related to existing meta-analyses in economics (e.g., Andrews and Kasy 2019; DellaVigna and Linos 2022), but we do so across topics rather than summarizing papers on one topic.

Fourth, we contribute to the large literature that uses life cycle models. Beginning with Gourinchas and Parker (2002), this literature has built rich models that incorporate a wide range of institutional features—such as portfolio choice, housing, retirement accounts, and social insurance—to match various patterns in household behavior. Our contribution is to introduce a broad set of behavioral frictions. This approach builds on Lusardi et al. (2017), who show that 30–40% of inequality in wealth at retirement is attributable to differences in financial knowledge. Relative to their work, which focuses on financial literacy, our paper takes a complementary approach of modeling the effects of many individual frictions that span financial, educational, health, and benefit-claiming decisions.

**Outline.** The remainder of the paper is organized as follows. The next section describes our framework for estimating the impact of each friction. We then present our estimates for each friction, grouped by category: education, savings, borrowing, insurance, benefits, and health. Section 3 aggregates the empirical evidence across all frictions and compares the magnitude of the losses to major government policies. The life cycle model is described and calibrated in Section 4, and counterfactual results are presented in Section 5. Section 6 concludes.

[2] Our paper is also related to the literature on the measurement of inequality, including Díaz-Giménez et al. (1997), Rodríguez et al. (2002), Kopczuk (2015), and Catherine et al. (2025).

[3] This approach builds on Stango and Zinman (2023), who provide evidence that many different biases are correlated with households' financial conditions.

# 1 Empirical Framework

In this section, we describe the empirical framework that we use in the first half of the paper. We begin by defining what we mean by a decision-making friction.

**Definition 1.** *A **friction** is a choice made by an individual that differs from the choice that would be made by a hypothetical individual in identical circumstances that optimizes normative utility with full information and no non-monetary decision costs.*

This definition is intentionally broad such that a friction could be driven by different microfoundations—such as a self-control problem, non-monetary costs, or imperfect information—about which we remain agnostic. This is because our goal is to estimate the financial impact of specific choices that we classify as frictions rather than evaluate the effects of specific policies (Hendren and Sprung-Keyser, 2020), measure the effects of specific biases (Stango and Zinman, 2023), or evaluate welfare implications (Bernheim and Taubinsky, 2018)—all of which require a microfoundation.

Importantly, a decision-making friction is not necessarily a mistake: the choice may be optimal from the perspective of the individual due to imperfect information or non-monetary decision (e.g., cognitive) costs (Bernheim et al., 2026).[4] In our applications, we focus on choices for which existing evidence suggests that they indeed reflect frictions.[5] For this reason, we deliberately omit choices that likely reflect non-standard preferences, such as gambling, which may be driven by anticipatory or entertainment utility (Lockwood et al., 2025). These choices would not satisfy Definition 1 because they would optimize normative utility. However, we acknowledge that not everyone will agree that all the frictions that we choose satisfy Definition 1. In this case, our framework provides estimates that can be interpreted as lower bounds on the (dollar-equivalent) utility gains that are required to rationalize choices across the income distribution.

Next, we describe how we estimate the financial impact of the frictions in Table 1. Consider a population of individuals denoted by $i$ that are observed at age $t$.[6] Let $j(i,t) \in \{\text{Low}, \text{Middle}, \text{High}\}$ denote the income group to which individual $i$ at age $t$ is assigned. Throughout the paper, Low, Middle, and High correspond to individuals in the bottom 25%, middle 50%, and top 25% of the distribution of a particular measure of income. Focusing on one friction in particular, we denote $s_{it} \in \{0,1\}$ as whether individual $i$ at age $t$ is in the population at risk for the friction and $f_{it} \in \{0,1\}$ as whether the individual is subject to the friction, with $f_{it} = 0$ whenever $s_{it} = 0$. For example, for the EITC claiming friction, $s_{it} = 1$ indicates eligibility and $f_{it} = 1$ indicates non-claiming; for the credit card late fees friction, $s_{it} = 1$ indicates having a credit card and $f_{it} = 1$ indicates paying a late fee. For some frictions, $f_{it}$ may be the result of past choices (e.g., attending a for-profit college early in life).

With this notation in hand, we now define how we measure the financial impact of a friction. By definition, the

[4] Our definition of a decision-making friction is equivalent to the definition of an improvable choice in Bernheim et al. (2026).

[5] In cases where the evidence is more ambiguous, we are conservative in classifying choices as frictions. For example, we do not classify all smoking as a friction; instead, we focus on smokers who report wanting to quit but do not. Similarly, for college attendance, we only classify non-attendance as a friction if it is driven by imperfect information.

[6] Throughout the paper, our analysis is done at the individual rather than household-level wherever possible.

flow budget constraint of an individual $i$ at age $t$ can be written as

$$\text{Consumption}_{it}(f_{it}) + \text{Wealth}_{i,t+1}(f_{it}) - \text{Wealth}_{it}(f_{it}) = R_{it}(f_{it}) \tag{1}$$

where $\text{Wealth}_{it}(f_{it})$ is wealth entering period $t$ before current-period asset returns are realized, $\text{Wealth}_{i,t+1}(f_{it})$ is wealth carried into the next period before next-period asset returns are realized, and $R_{it}(f_{it})$ is current-period consumable income available to finance consumption and net savings. Under this timing convention, current-period capital income is included in $R_{it}(f_{it})$ rather than in the change in wealth. Using (1), we define the financial impact as follows.

**Definition 2.** *The **financial impact** of a friction for individual $i$ at age $t$ is defined as*

$$l_{it}(f_{it}) \equiv R_{it}(0)\, A_{it}(0) - R_{it}(f_{it})\, A_{it}(f_{it}) \tag{2}$$

*where $A_{it}(f_{it}) \in \{0,1\}$ denotes whether the individual is alive, which can be affected by the friction.*[7]

Equation (2) captures the change in consumable income in a counterfactual in which we "turn off" the friction of interest. While this definition is useful for quantifying the impact of each friction, it is subject to two limitations. First, it may not be feasible to turn off frictions individually to the extent that they are driven by similar micro-foundations. Second, by writing the financial impact as a function of $i$ only, we implicitly ignore any spillovers or general equilibrium effects associated with turning off the friction.

Estimating $l_{it}(f_{it})$ empirically requires constructing consumable income, $R_{it}(f_{it})$. Since consumption and wealth, which define $R_{it}$ in (1), are not observable, we estimate $R_{it}(f_{it})$ by constructing and summing each of its components:

$$R_{it}(f_{it}) = \text{Labor Income}_{it}(f_{it}) + \text{Capital Income}_{it}(f_{it}) + \text{Benefits}_{it}(f_{it}) - \text{Taxes}_{it}(f_{it}) - \lambda_{it} f_{it} \tag{3}$$

where $\lambda_{it}$ is any direct dollar loss associated with the friction. In practice, constructing the components of $R_{it}(f_{it})$ in (3) involves assumptions and approximations that may cause it to differ from (1), which we discuss when we describe each friction in Section 2.

An important feature of this framework is that it allows the financial impact of different frictions to have distinct channels. For example, attending a for-profit college reduces $\text{Labor Income}_{it}$, paying credit card late fees creates a loss through $\lambda_{it}$, stock market non-participation lowers $\text{Capital Income}_{it}$, and not claiming EITC lowers $\text{Benefits}_{it}$. While health frictions also have direct losses through $\lambda_{it}$ (e.g., the cost of cigarettes), an important distinguishing feature of these frictions is that their financial impact also depends on a mortality effect: if removing a health friction causes an individual to live longer such that $A_{it}(0) = 1$ but $A_{it}(f_{it}) = 0$, the individual will have positive

[7] When computing $l_{it}(f_{it})$, we hold fixed the income-group assignment of each individual-age observation. If an individual is alive only when $f_{it} = 0$, we assign the observation to an income group using the relevant measure of income with $f_{it} = 0$ and the age-specific income cutoffs in the observed environment.

instead of zero consumable income for more periods, and we compute the impact of the friction as this forgone income.

Finally, we define the following key objects that we estimate separately for every friction in Table 1. We measure these objects separately among individual-age observations in each income group, $j$. All probabilities and expectations below are taken over the full set of individual-age observations given the empirical distribution of $f_{it}$, with relevant conditioning made explicit.

**Definition 3.** *For each friction and income group $j \in \{\text{Low}, \text{Middle}, \text{High}\}$,*

1. *The **share at risk**, $S_j$, is the share of alive individual-year observations in group $j$ for which the friction is relevant:*

$$S_j \equiv \mathbb{P}\left(s_{it} = 1 \mid A_{it}(f_{it}) = 1, j(i,t) = j\right). \tag{4}$$

2. *The **friction prevalence**, $F_j$, is the share of at-risk alive individual-year observations in group $j$ with the friction:*

$$F_j \equiv \mathbb{P}\left(f_{it} = 1 \mid s_{it} = 1, A_{it}(f_{it}) = 1, j(i,t) = j\right). \tag{5}$$

3. *The **average loss**, $L_j$, is the total financial impact of the friction among individual-age observations in group $j$, divided by the number of affected individual-years observed under the friction:*

$$L_j \equiv \frac{\mathbb{E}\left(f_{it} l_{it}(f_{it}) \mid j(i,t) = j\right)}{\mathbb{E}\left(A_{it}(f_{it}) f_{it} \mid j(i,t) = j\right)}. \tag{6}$$

4. *The **unconditional loss**, $\Delta_j$, is the total financial impact of the friction among individual-age observations in group $j$, divided by the number of individual-years observed under the friction:*

$$\Delta_j \equiv \frac{\mathbb{E}\left(f_{it} l_{it}(f_{it}) \mid j(i,t) = j\right)}{\mathbb{E}\left(A_{it}(f_{it}) \mid j(i,t) = j\right)} = S_j F_j L_j. \tag{7}$$

5. *The **percent average loss** and **percent unconditional loss** are defined as $L_j / \overline{R}_j$ and $\Delta_j / \overline{R}_j$, respectively, where*

$$\overline{R}_j \equiv \mathbb{E}\left(R_{it}(f_{it}) \mid A_{it}(f_{it}) = 1, j(i,t) = j\right). \tag{8}$$

To understand the definition of $L_j$, consider a simpler case in which the friction does not affect mortality. In this case, $A_{it}(0) = A_{it}(f_{it})$ and (6) simplifies to

$$\begin{aligned} L_j &= \frac{\mathbb{E}\left(A_{it}(f_{it}) f_{it} \left(R_{it}(0) - R_{it}(f_{it})\right) \mid j(i,t) = j\right)}{\mathbb{E}\left(A_{it}(f_{it}) f_{it} \mid j(i,t) = j\right)} \\ &= \mathbb{E}\left(R_{it}(0) - R_{it}(f_{it}) \mid f_{it} = 1, A_{it}(f_{it}) = 1, j(i,t) = j\right). \end{aligned}$$

Therefore, for frictions that do not affect mortality, $L_j$ is simply the average financial impact among affected individuals that are alive. In contrast, for frictions that affect mortality, part of the impact of the friction comes from

changing the set of individuals that are alive. The definition in (6) captures this effect by summing the financial impact among *all* individual-age observations and dividing by the number of affected individual-ages *observed* with the friction. For example, if the only effect of removing a friction is that affected individuals live one additional period, $L_j$ is the consumable income of individuals who would otherwise have died in these additional periods, divided by the number of affected individual-years observed under the friction.

In some cases, we compute age-specific versions of the objects in Definition 3 by conditioning on age $= t$, which we denote by $S_{jt}$, $F_{jt}$, $L_{jt}$, and $\Delta_{jt}$. Defining $\omega_{jt} \equiv \mathbb{P}\left(\text{age} = t \mid A_{it}(f_{it}) = 1, j(i,t) = j\right)$ as the empirical share of observed alive individual-year observations in income group $j$ that occur at age $t$, we have:

$$S_j = \sum_t \omega_{jt} S_{jt}, \qquad F_j = \sum_t \frac{\omega_{jt} S_{jt}}{S_j} F_{jt}, \qquad L_j = \sum_t \frac{\omega_{jt} S_{jt} F_{jt}}{S_j F_j} L_{jt}, \qquad \Delta_j = \sum_t \omega_{jt} \Delta_{jt} = \sum_t \omega_{jt} S_{jt} F_{jt} L_{jt}.$$

We leverage these relationships to construct the objects in Definition 3 for some frictions below, ensuring that we always use the same $\omega_{jt}$, even though the data sources differ across frictions.

**Empirical implementation.** When implementing this framework empirically, we try to be as consistent as possible across frictions with respect to the following choices. First, our baseline estimates of the objects in Definition 3 are in the 2010s; in additional analyses described in Section 3, we consider the evolution over time for a subset of frictions. Second, wherever possible, we define income groups based on age-specific distributions of pre-tax pre-transfer income, defined as the sum of labor and capital income in working life and social security benefits and capital income in retirement. Third, we only try to capture the "mechanical" financial impact of removing a friction, ignoring any endogenous responses (e.g., increased savings in response to higher returns). As described below, we attempt to capture these endogenous responses more fully in our life cycle model.

**Comparison with life cycle model.** An important benefit of this empirical approach is that it does not require assumptions about (i) the correlation of different frictions within-individual (e.g., whether individuals who smoke are also more likely to pay late fees)[8], (ii) the auto-correlation of a given friction within-individual, or (iii) individuals' sophistication about the prevalence of frictions. In Section 4, we incorporate each of these frictions into a structural life cycle model. This analysis, which requires taking a stand on each of these dimensions, is complementary to the empirical approach for three main reasons. First, translating all of the frictions in this section into losses in consumable income requires simplifying assumptions that we can relax in the life cycle model by modeling some of the frictions directly. Second, the model allows us to capture additional forces that affect the financial impact of each frictions, including endogenous responses to turning off each friction, interactions between frictions, and dynamic effects. Finally, through endogenizing consumption-savings decisions, our model allows us to study the effects on consumption and wealth inequality.

[8]There are a couple of exceptions in which we make explicit assumptions on the correlation structure of frictions within a category to aggregate them into one friction. For example, for college attendance, the evidence suggests there are multiple underlying frictions at play, so we assume a correlation between these frictions to combine them into one friction.

# 2 Measuring the Prevalence and Losses of Frictions

In this section, we go through each of the frictions in Table 1 and describe in detail how we compute $S_j$, $F_j$, and $L_j$, grouping frictions into subsections based on the behavior that they affect. The corresponding results are shown in Table 3, with an overview of our computation for each friction shown in Table 2. Where possible, we also compute confidence intervals, with additional details reported in the Appendix. We summarize this evidence in section 3.

This section focuses on the description of each friction and their prevalence across 2010 - 2019 (with all dollar estimates inflated to 2020 dollars). For a subset of frictions, we also document their evolution over time, from the late 1990s/early 2000s to the 2010s and the early 2020s. Unless stated otherwise, we form the income groups using the pre-tax and pre-benefit income as measured in the year of the survey. Further detail is provided in subsection 3.6.

Figure 4 and Table D1 summarize these results, with further details provided in each friction's appendix.

## 2.1 Education Frictions

### 2.1.1 Not Attending College Due to Frictions

We use Snyder et al. (2019)'s estimate of the proportion of people that don't attend college by parental income group. We aim to estimate the share of low-income, middle-income, and high-income students who do not attend college due to behavioral barriers. Throughout, we define low-, middle-, and high-income students as the bottom 20 percent, middle 60 percent, and top 20 percent of the parental-income distribution, respectively. We also estimate the average returns to attending (higher-quality) college. We premise that it is difficult to separate behavioral frictions from financial frictions.

We first estimate the share of people that do not attend college due to a behavioral friction among low-income, middle-income, and high-income individuals (split by parental income). A motivating piece of evidence is that, even conditioning on test scores or grades, the rates of college attendance differ significantly by income proxies. In Table E1 we use the 2009 High School Longitudal Survey (HSLS) and regress attendance to any college on parental income groups, controlling for academic GPA deciles, as well as deciles of a math cognitive test. Comparing the high-income group to the low-income group, we estimate a 12.7 percentage point difference in college attendance. Adding additional controls leads to a *larger* difference.[9] The estimate for the middle-income group (relative to the low-income group) is slightly less than half the estimate for the high-income group. We acknowledge that this comparison captures both behavioral and financial frictions.

Several experiments present direct evidence on behavioral frictions to college attendance. Bettinger et al. (2012) presents the results of an RCT in which low-income tax filers at H&R Block in the treatment group were helped to complete the FAFSA form using information that was already present for tax filing, resulting in an 8.1 percentage point (s.e. = 3.5) impact on college attendance one year later. Dynarski et al. (2021) is an RCT which

[9] A related set of descriptive findings is from Hoxby and Avery (2012) documenting that low-income students for given grades apply to fewer colleges and especially fewer selective colleges (where they could be admitted).

targets low-income, high-grades students in Michigan letting them know that they would have a free ride at the University of Michigan, leading to a 7.2 percentage point (s.e. = 2.2) impact on enrollment at 4-year selective colleges. Barr and Castleman (2025) document that a mentoring RCT during senior year in high school (about 10 hours per student) leads to a 9.1 percentage point (s.e. = 2.0) increase in 4-year college enrollment, while Oreopoulos and Ford (2019) finds a 5.2 percentage point (s.e. = 1.3) increase in college enrollment in response to mentoring during the college application, for an average precision-weighted impact of 6.4 percentage points (s.e. = 1.1).[10]

Importantly, not all such interventions have a sizable impact. Most interventions in the US that provide just information lead to null results or very small impacts. For example, Bird et al. (2021) find that a large-scale messaging RCT encouraging students to apply to FAFSA did not have an impact on college application. In contrast, the above studies provide more than a generic encouragement in the form of mentoring, a guarantee of admission, or the chance to complete the FAFSA in one seating. We still code them as behavioral frictions as the time cost or effort involved is small compared to the lifetime returns.

The papers above identify three different behavioral frictions in attending college – obstacles in filling the FAFSA form, lack of mentoring in the senior year of high school, and poor information about the admission (and cost) of public universities.[11] These factors operate largely independently, though there are overlaps, e.g., mentoring could certainly include FAFSA help. To compute the share of low-income students affected by at least one of the frictions, we need to specify how correlated the three frictions are. For example, under the assumption of no correlation we would estimate an aggregate impact of 20.2 percentage points (s.e. 3.6), while under the assumption of perfect correlation, we would estimate an impact of 9.1 percentage points (s.e. 2.3). Based on the evidence in Table 4 on the correlation across frictions, we assume a correlation of 0.032 and compute a precision-weighted average of 20.1 percentage points (s.e. 3.7). Given that the proportion not attending college ($S_j$) among the low-income students is 0.405, the implied share with a friction ($F_j$) is estimated to be 0.201/0.405 = 0.323 (s.e. ).

To construct comparable estimates for the middle- and high-income groups, we vary the set of interventions assumed to apply to each group. For low-income students, we include mentoring, FAFSA assistance, and information about free tuition. For middle-income students, we include mentoring and FAFSA assistance, while for high-income students we include mentoring only. Under our assumed correlation of 0.032 across frictions, these combinations imply total effects ($T_j$) of 20.1, 13.9, and 6.4 percentage points for the low-, middle-, and high-income groups, respectively. For all three groups, we calculate the friction rate as ($F_j = T_j / S_{\text{low}}$), where ($S_{\text{low}}$) is the share of low-income students who do not attend college. We use the low-income non-attendance rate in the denominator because the experimental estimates are obtained largely from low-income populations and therefore identify the share of that population moved into enrollment. Differences across income groups enter through ($T_j$), since different interventions are assumed to apply to each group. Thus the ratio $T_j / S_{\text{low}}$ is the fraction of the non-enrolled that the group-$j$ interventions persuade into enrollment. Because $T_j$ uses only the interven-

[10] Separate evidence suggests that mentoring programs can increase the graduation rate. An RCT on Community Colleges in Ohio called ASAP estimated raising completion of community college by 25 percentage points (Hill et al., 2023).

[11] We note that the returns estimates reported above are for attending college, not completing college, and are thus consistent with the outcome variable examined for the three frictions.

tions appropriate for group $j$, we argue that this persuasion rate is the one that would apply to group $j$. Dividing instead by each group's own ($S_j$) would extrapolate the experimental estimates to populations not directly studied and would mechanically raise the implied friction rate for groups with lower non-attendance. This procedure gives estimates of (0.275) (s.e. ()) for the middle-income group and (0.224) (s.e. ()) for the high-income group. We also provide additional details of how we modify our estimates of $S$ and $F$ to fit the lifecycle model and how we construct confidence intervals in subsection E.1.

We note that these estimates do not include other behavioral frictions that also stand in the way of higher education, e.g., the evidence of Hastings and Weinstein (2008) and Cohodes et al. (2025) for middle-school students.

Next, we present the evidence on the financial losses from not attending college, which translates into the loss parameter $L_j$. While there are hundreds of estimates on returns to college, which broadly estimate a 8-12 percent return per year of college attended, we use four main papers, all using regression discontinuity designs, to identify the return for the marginal college attender largely from low-income groups. Hoekstra (2009) estimates a 22 percent (s.e. = 8) earnings increase due 10 to 15 years after admission to a selective state college. Zimmerman (2014) estimates a 22 percent (s.e. = 11) return 8 to 14 years after the college admission to a Florida college. Smith et al. (2025) for Georgia estimates a 17 percent (s.e. = 10) return to attending a 4-year public college by age 30; notably, the estimate is higher (around 30%) for low-income students. Mountjoy (2025) estimates a return to attending selective public colleges in Texas of 8.6 log points (s.e. = 3.2) in years 8-12 after admission. The different estimates are actually consistent, as the papers estimate returns of 9-11 percent per extra year of college attended, with the differences due variation in the extra years of schooling induced by admission, e.g., 1 year in Mountjoy (2025), but 3 years in Zimmerman (2014). We take the precision-weighted average and estimate an average return of 12.0 percent (s.e. = 2.8), which we assume is only earned after age 26. This constitutes our estimate of the loss $L_j$, together with estimates of additional debt and lost earnings due to college attendance, as detailed in the subsection E.1.

For the counter-factual that removes the friction, for a share $F_j$ of the high-school graduates we increase earnings, add debt and lower the initial wealth (to compensate for the lower earnings while attending college). Table 3 provides a summary of the estimates.

**Notes and Caveats.** There are a number of caveats. First, to estimate the share with a friction we aggregate across papers, which involves some arbitrariness. Second, it is hard to draw a firm line between behavioral frictions and frictions that have a cost component. Third, we do not model the fact that, if significantly more low-income individuals were to apply to selective colleges, college attendance by other groups would be crowded out, or potentially the college wage premium would be reduced. Fourth, while we have multiple estimates of the returns to college over the next 5-10 years, we do not have estimates of the long-term returns; we assume a constant return.

### 2.1.2 Attending 2-Year For-Profit Colleges

We summarize evidence that on average attending a community college instead of a 2-year for-profit college leads to higher earnings and lower debt accumulated. Given that community colleges are available nearly uniformly across the US, we identify attending a 2-year for-profit college as a behavioral friction.

We measure the proportion of students attending any college by parental income using Snyder et al. (2019), and we determine the proportion of students who attend 2-year for-profit colleges using the 2012/17 Beginning Postsecondary Students survey (BPS, 2017). The BPS income groups are the bottom 20 percent, middle 60 percent, and top 20 percent of the weighted parental-income distribution among dependent students. As Table E2 shows, in the low-income group, 8.0% of students go to a 2-year for-profit college, compared to 2.4% in the high-income group. The attendance to a 2-year public or non-profit college is instead fairly similar across income groups. Thus, the share of 2-year college attendance that is to a for-profit college, our estimate of $F_j$, is much higher for low-income students (0.151) than for high-income students (0.078). subsection E.2 provides additional details on the estimates of $S$ and $F$.

Regarding the loss $L_j$ from 2-year for-profit college attendance, Cellini and Turner (2019) uses administrative data, merged with 1999-2014 IRS tax data, to study outcomes of federally aided students who exited postsecondary institutions between 2006 and 2008. Using the matched comparison of students who attend a 2-year for-profit college to students attending a 2-year public college, they find that i) students who attended a for-profit college are 1.5 percentage points (s.e. = 0.6) less likely to be employed and, conditional on employment, have an income that is 11.3 log points (s.e. = 1.1) lower than others who attended a public/non-profit college, and ii) 83% of for-profit students have debt, comparing to 23% in a matched sample of public school students, and the average total debt amount is $6,091 for the for-profit students, compared to $1,205 for matched public school students.

Two additional papers provide concurring evidence. Comparing for-profit students against a matched sample of public university students, Deming et al. (2012) find that students of for-profit colleges took out $3,417 more in Title IV loan and grant aid in 2003-2004, were 6.7% more likely to be unemployed and seeking work in 2009 and were earning 6.77% less relative to 4-year public and non-profits. For-profit students were also 5.1% less likely to attain their degree. Armona et al. (2022) find that students who attend 2-year for-profit institutions take on $6,428 more in loans and, 6 years after graduating, make $8,541.20 (or 36.27%) less than their public sector counterparts.

We estimate the average annual loss $L_j$ using the evidence from Cellini and Turner (2019) on earnings loss, higher unemployment probability, and higher debt levels for those who attend for-profit colleges.[12]

**Other Notes and Caveats.** We note three important caveats. First, we assume that the earnings loss from attending a 2-year for-profit college lasts for the entire working life. While Cellini and Turner (2019) only has evidence for 6 years post attendance, the event study figure indicates if anything that the earnings loss increases over time. Second, the estimates for earnings losses refer to the 2006-08 period, and may differ for periods with a more positive economic environment. Third, our calculations do not incorporate the fact that for-profit colleges, while on average having lower returns, may be more convenient or a better match for a subset of students.

[12] Cellini and Turner (2019) estimate that attendance to a 2-year for-profit college leads to a higher average debt level of $0.83 * \$6,091 - 0.23 * \$1,205 = \$4,778.38$, which equals $5,965 of additional debt in 2020 dollars. These estimates are roughly consistent with 2019-20 administrative data on student loans. Per the NCES (2023), 76% of 2-year for-profit college attendees take out an average of $8,353 in annual student loans, while 18% of other 2-year college attendees take out an average of $5,185 in annual student loans, giving us an annual difference of $5,421 in student loans. We note that the friction identified in Cellini and Turner (2019) is attending a 2-year for-profit college, not graduating. Since only about half of students get a 2-year degree, the use of annual debt levels is appropriate.

## 2.2 Savings Frictions

### 2.2.1 Not Meeting the Employer 401(k) Match

Retirement savings in the form of Defined Contributions such as 401(k)s are, together with home equity, the most important assets for most US households. These plans have tax-advantaged status, with pre-tax contributions, taxation at withdrawal, and no taxation of capital gains. In addition, the majority of employers that offer 401(k)s provide an employer match, most commonly a 50 percent match on contributions up to 6 percent. Given these advantages, the limited role of Social Security and the declining share of Defined Benefit plans, participation in Defined Contribution accounts is typically seen as a critical step to save for retirement.

Yet, a number of papers, starting with Madrian and Shea (2001); Choi et al. (2004), document that participation in 401(k) plans is partial and depends significantly on the default, with larger default effects for employees with lower pay (Madrian and Shea, 2001). While the default effects attenuate significantly over employee tenure, as individuals in the opt-in default increase their participation (Choukhmane, 2025), a difference is often still detectable 2 years since the start of employment. These findings suggest that lack of participation in 401(k)s, at least to an extent, is due to behavioral frictions such as procrastination and limited attention.

We model the failure of taking full advantage of the employer match as a behavioral friction. We measure the share $S_j$ eligible for the 401(k) decision, that is, workers employed in companies that offer a 401(k) plan, using data from Bureau of Labor Statistics (2020a). The share of workers eligible for a 401(k) is 0.46 in the low-income group and 0.86 in the high-income group. The corresponding estimates of $S_j$ in Table 3 are lower as those estimates are calculated at the person-year level, and in our model, individuals are not eligible for contributing to a 401(k) account in retirement. The share of workers who do not take full advantage of the match, our measure of $F_j$, from Carranza et al. (2026), is 0.57 for the low-income group but only 0.20 for the high-income group.

To measure the extent of the loss $L_j$, we compute it as the missed match, that is, 3 percent of the annual labor earnings for the case of no participation and 1.5 percent of the earnings for the case of partial participation. subsection F.1 details how we use information on 401k participation from Bureau of Labor Statistics (2020a) to determine the proportion of people who perform no vs partial contributions. The same appendix also details how we calculate confidence intervals for this friction.

**Notes and Caveats.** First, we assume that lack of 401(k) participation is a behavioral friction, while for constrained households it can be an optimizing decision. Still, even employees who are liquidity constrained could invest, receive the match, and then disinvest (at a 10 percent penalty below the age of 59 and no penalty otherwise). Second, the measure of loss does not account for the tax benefits of 401(k) or the equity premium on the returns. In the model, we account for realistic features of 401(k) investment, such as average vesting and investment returns.

### 2.2.2 Not Investing in Stock Mutual Funds

Given the consistent equity premium over the last century in the US, not participating in the stock market leads to significantly lower returns to savings. Since lack of participation in equity markets could also be due to

lack of savings or fixed costs to invest, we define the population at risk $S_j$ as the share of the population with liquid savings plus defined-contribution savings above the highest of 2 months of pre-tax salary and $2,000. Our $2,000 floor is close to the $2,467 liquid-savings threshold that Sabat and Gallagher (2019) estimate households should hold to guard against financial distress, but we conservatively take the maximum of this floor and 2 months of salary because their estimate is based on a sample of entirely low-income households, which biases us against finding that the frictions are regressive.[13] As Figure C1a shows, this share is about twice as large in the high-income group than in the low-income group, though even in this latter group it hovers around 40 percent.

To measure the prevalence $F_j$ of the friction, we compute the share of the population, among those with enough wealth to invest in equity, that does not have any equity participation, in either their liquid assets or their DC plans.[14] As Table 3 reports, the lack of stock market participation is very high for the low-income group, at 0.646 and is much lower for the high-income group, at 0.129.

To measure the impact $L_j$ of the friction, we need a counterfactual for the share invested in the stock market. We take as counterfactual the share invested in equity by consumers with positive stock market participation, 41 percent for the low-income and the middle-income group, and 43 percent for the high-income group. To estimate the loss $L_j$, we multiply this share by the average financial wealth (including DC wealth) and by the average equity premium.[15] We assume an average stock market equity premium of 5 percent as in Gomes (2020), but we adjust this estimate downwards for investors potentially investing in underdiversified stocks or high-fee mutual funds.

**Notes and Caveats.** We made a set of conservative assumptions. First, we winsorize the losses at the 95th percentile to avoid positive outliers. Second, we do not take into account the fact that the extra savings in equity grow exponentially year after year. Third, we use as benchmark for optimal equity investment the observed equity share at around 40 percent; the results from Choukhmane and de Silva (2026), which we use in the model implementation, suggest a significantly higher equity share conditional on participation.

### 2.2.3 Saving in Low Interest Accounts

A long-standing literature documents that the interest rates banks pay on deposits sit well below the policy rate (Hannan and Berger, 1991; Neumark and Sharpe, 1992), and that the pass-through from policy rates to deposit rates is incomplete, with deposit rates rising less than one-for-one with the policy rate (Drechsler et al., 2017). Several papers have argued that one reason for this incomplete pass-through is depositor unsophistication and inattention, which causes households to not respond to the spread between deposit rates and available market rates (Argyle et al., 2024; Eichenbaum et al., 2025; Egan et al., 2026; Benetton et al., 2026). This is consistent with evidence that more financially literate and attentive households hold fewer low-yield deposits (Deuflhard et al., 2019; Lu and Wu, 2026). Motivated by this evidence, we define as a friction holding a sizable amount of wealth in low-interest checking and traditional savings accounts despite such accounts offering very low interest rates.

[13] This threshold is also close to the typical monthly expenses that households incur: Greene and Stavins (2022) report that monthly expenses on bills and purchases average 77 percent of households' liquid assets. It is likewise on the order of estimates of the cash expenditures that households cannot pay by credit card (Telyukova 2013, Table 8).

[14] individuals that only hold an under-diversified equity portfolio, that is, hold up to 5 individual stocks, are not counted as invested in equity.

[15] We winsorize individual losses at the 95 percent level to minimize the impact of possible outliers, as can be seen in Figure F1.

Using the 2013-2019 SCF data, we measure (i) the population $S_j$ at risk as the proportion of consumers with non-retirement wealth above the maximum of 2 months salary and \$2000, and (ii) the population $F_j$ affected by the friction as the proportion with total wealth in checking and traditional savings accounts greater than the maximum of 2 months salary and \$2000. Figure C1b shows how $S_j$ and $F_j$ vary with age and income groups for this friction. We calculate $L_j$ as the increased annual returns if consumers moved their holdings in checking and savings account (beyond the minimum) to a money market fund. We calculate the increased annual returns using the 2013-2019 market yield on U.S. treasury securities (73.6 basis points, The U.S. Federal Reserve (2026)).

**Notes and Caveats.** We assume that consumers do not need to hold greater than the maximum of 2 month's salary and \$2,000 as liquid wealth based on the evidence in Sabat and Gallagher (2019) summarized above.

#### 2.2.4 Investing in Individual Stocks

A tenet of portfolio choice is that investors should build well-diversified portfolio to avoid incurring idiosyncratic risk, and yet individuals investors often hold individual stocks. For example, Goetzmann and Kumar (2008) documents how common under-diversification is among US investors using data from the 1990s and, using Dutch data, Gaudecker (2015) documents a similar large extent of under-diversification.

There are two important caveats. In the last two decades, the choice of mutual funds has become more common, reducing the importance of under-diversification as measured in the papers above. Second, the choice of individual stocks is uncommon in Defined Contribution plans, which account for most equity holdings in the US.

To measure the extent of under-diversification, we use 2013-19 SCF data to measure the holding of individual stocks in the non-retirement liquid savings (assuming no such holdings in retirement DC plans). We thus measure the share $S_j$ at risk of the friction as the share with financial assets (excluding retirement accounts) larger than the maximum of \$2,000 or two months of income. As Figure C1c shows, the share is between 30 and 60 percent (depending on age) for low-income individuals, and is as high as 90 percent for high-income individuals.

Next, we measure the incidence of the behavioral friction $F_j$ as the share of individuals that hold at least 50% of their non-retirement wealth in 5 or fewer directly held stocks. As Figure C1c shows, the share is highest for the high-income group, hovering around 6 percent, and is as low as 1-3 percent for the low-income group.

We now describe the measure of the loss $L_j$. Since the SCF does not report the exact stocks, only how many stocks an individual holds, we assume that individuals hold a randomly selected set of $N$ US stocks with equal weights. Under this assumption, the expected return on this portfolio equals the market's expected return, so all of the loss come from an increase in volatility, which, under the CAPM, we estimate using the variance of the market portfolio and the average variance of an individual stock. We then compute the certainty-equivalent return reduction of this loss using the Arrow-Pratt approximation, assuming a coefficient of relative risk aversion of 2.5 (following Choukhmane and de Silva 2026). Finally, we convert into a dollar loss by multiplying the certainty-equivalent return reduction by the dollar holdings of individual stocks (see Section F.4 in the appendix for the full derivation). We winsorize the dollar losses at the 90th percentile to minimize the impact of outliers (Figure F3).

Table 3 shows that the loss is sizable. For example, in the middle-income group for the share with positive

savings that is under-diversified, the average investment in individual equity is $53,000, implying a loss due to excess volatility (winsorized at the 90 percent) of $1,446.

**Notes and Caveats.** Like for other frictions, we aim to make conservative assumptions. We set the threshold for the friction at an investment in individual stocks of at least 50% of wealth. In practice, this does not matter much as setting a lower threshold adds individuals who tend to have a small loss, as Table F1 and Table F2 show. We also exclude from the friction the choice of individual stocks in DC plans, such as employer stock. While the latter investment used to be common, it has become less so following the passage of the Pension Protection Act of 2006, which required employers to allow workers to move their stock into diversified options (Parker et al., 2025). Finally, we focus on the losses associated with underdiversification rather than poor stock selection or high turnover both of which reduce average net of fee returns. While existing literature highlights that these behaviors are prevalent in brokerage accounts (Odean, 1999), a relatively small share of households have brokerage accounts and, for those who do, these accounts are not a large fraction of total financial wealth (Bilias et al., 2010; Gomes et al., 2021).

#### 2.2.5 Investing in High-Fee Mutual Funds

Over time, individuals investors have shifted more of their investment towards mutual funds. While this limits the losses due to under-diversification, it makes the choice of mutual funds with low fees especially important. Hortaçsu and Syverson (2004) document that even for simple mutual fund classes such as S&P 500 funds, there is a wide dispersion in fund fees, consistent with investors not paying attention to the fees. Choi et al. (2010) offer participants in a laboratory setting the choice among different S&P 500 mutual fund plans, each presented with realistic prospectus features. The choice of plan almost entirely disregards the mutual fund fee, with investors focusing instead on returns since inception (which differs across plans due to different dates of inception).

We first compute the share $S_j$ with investments in mutual funds, including both non-retirement and retirement accounts. As Figure C1d shows, this share is significantly higher for the higher-income group, reaching 90 percent in late middle age, while for the low-income group it hovers around 20 percent.

Turning to the share $F_j$ who do not pay attention to the fees, Choi et al. (2010) show that, even when presented with a reminder of fees, only 9 percent of staff participants allocate all the portfolio on the low-fee fund. They also show that the choice of fees is orthogonal to education or SAT test scores. Based on this, we assume $F_j = 0.91$ for all three groups. This assumption is arguably conservative as the share investing entirely on the low-fee fund is nearly zero when subjects see just the fund prospectus, and it rises to 9 percent only after the fees are made salient.

To quantify the loss $L_j$, we measure the average mutual fund fee, in excess of the minimal fee. This is the average extra fee that consumers with the friction pay. We use the mutual fund data base from the Center for Research in Security Prices (2026) (CRSP) from 2011 to 2019, computing for each fund category (as defined by the CRSP style codes) the average fee and the 20th percentile fee. We then weight across the categories by the total net assets to compute that across all stock and mixed-fund categories, the 20th percentile fee is 18.38 basis points and the mean is 57.74 basis points,[16] for an average excess fee of 39.36 basis points. We multiply this excess fee by the

[16] This mean fee is much lower than the one documented in Hortaçsu and Syverson (2004), reflecting the stark decline in fees since the 1990s.

wealth invested in mutual funds, winsorizing at the 95th percentile, as illustrated in Figure F4.

**Notes and Caveats.** Even within a narrow fund category, there can be variation in the exact investments, and investors may optimally choose a fund with a higher fee because of a preference for other product characteristics. Relatedly, investors may have access only to a limited set of mutual fund families in their DC investment and may thus not be able to pick a low-fee fund even if they wanted to. To partially address these concerns, we assume that individual investors only have access to funds at the 20th percentile of all mutual fund fees.

## 2.3 Borrowing Frictions

### 2.3.1 Not Refinancing a Mortgage

Most home-owners in the US take mortgages with fixed interest rates (typically at a 30-year horizon). For such mortgages, if the interest rate dips to a value low enough, an optimizing consumer will refinance the mortgage to a lower interest rate (taking into account refinancing time and monetary costs).

A number of papers document inertia in refinancing. Keys et al. (2016) use US data from a million mortgages from 2010 and quantify a monthly loss of $184 for the 20 percent of households who they estimate should be refinancing but do not. Andersen et al. (2020) use administrative Danish data to produce their key finding, reproduced in Figure G1. On the x-axis is the incentive to refinance, defined as the difference between the interest rate of the mortgage currently held and the current interest rate, minus the (estimated) fixed costs of refinancing. The histogram bars display the distribution of the incentives. If households always refinanced whenever optimal, we would not observe cases with positive incentives (beyond the initial year). Instead, we observe a thick right tail of loans that are not refinanced despite substantial incentives. Second, the line shows the probability of refinancing in a given quarter as function of the incentives. Under the standard model, such probability should be zero for negative incentives, and close to 1 for positive incentives. In the data, the probability is indeed near zero for negative incentives, but for positive incentives it only peaks at 12-13 percent, indicating a high incidence of inertia.[17]

Using data from the SCF, we determine $S_j$ as the share of households who own a house and have a (fixed-rate) mortgage. As Figure C1e reports, the share peaks around age 50 and is significantly higher for the high-income group than for the low-income group, which is much more likely to be renting. The figure also shows that the mortgage (in dollars) for households which take a new mortgage is significantly larger for high-income households.

The second parameter is the share $F_j$ of households with a mortgage who display a friction and do not refinance even when optimal. Andersen et al. (2020) assume that households have a probability $p$ of being asleep in each quarter, which is i.i.d. over quarters. Taking their estimate of Model 3 in Table 2 and Figure 9a, we estimate that low/middle/high income households have an i.i.d. chance of 96%/92%/91% of being asleep in each quarter, which we translate into a probability of being asleep for a whole year, $p^4$, e.g., $0.96^4 = 0.85$ for the low-income group.

The third parameter is the loss $L_j$, which we compute with a set of simulations. We generate draws of interest rates using a process fit to the US interest rate from 1961 to 2024, as described in subsection G.1. We assign house-

[17] The fact that the refinancing likelihood actually *decreases* at higher incentive levels suggests that some households are systematically more likely to remain "asleep" than others. These households are more likely to be found among households with very high incentive to refinance.

holds to get a mortgage following the empirical proportions in Figure C1e, interpolated to cover every year of age and take the size of the mortgage from Figure C1e for that income-age group. We compute the mortgage payment using a mortgage calculator assuming the average mark-up (relative to market rates) for that income group.

Once a household has a mortgage, a household 'wakes up' and checks for refinancing opportunities each year with an i.i.d. probability $1 - F_j$ and refinances if optimal. We implement the Agarwal et al. (2013) square-root rule for the optimal threshold value of the difference in the current interest rate and interest rate of the mortgage (see subsection G.1 for the formula and parameter definitions). If a household finds it optimal to refinance, they pay the refinancing cost and refinance to a mortgage with a new 30-year duration, but with the lower interest rate.

We compute the loss $L_j$ by comparing the two scenarios, one with households refinancing optimally ($F_j = 0$) and one in which consumers are subject to the i.i.d. friction $F_j$. For all periods in which the two scenarios yield the same mortgage repayment, the loss $L_j$ is zero. In all periods in which instead the awake household has refinanced but the one with friction has not, we compute the difference in the mortgage payment across the two scenarios, including the refinancing cost. For each simulated household who purchases a house, we compute the lifetime sum of the net losses due to inattention in mortgage payments[18] and divide by the total number of years with a mortgage. Finally, since our model is at the individual and not household level, we divide this annual net loss by 1.53 to account for married vs unmarried households, using data from the 2020 US Census.

**Validation.** Using this simulation, we reproduce the key figure from Andersen et al. (2020). As Figure G2 shows, we fit the patterns reasonably well, despite the fact that we are using US, as opposed to Danish, parameters. We also reproduce the estimate of Keys et al. (2016) that, conditional on refinancing being optimal, households would on median save \$184*12=\$2,208 per year by refinancing. In our sample, we compute a saving of \$2,367 per year.

**Notes and Caveats.** First, our model is a simplified version of the one in Andersen et al. (2020), and in particular it does not model psychological switching costs. In subsection G.1 we estimate a model with income-specific sleep probability and income-specific psychological switching cost, translating the estimates from the Andersen et al. (2020) paper from Danish Kroner into dollars. The patterns are similar, with a loss 10 to 30 percent lower than the benchmark one. We use the model without psychological costs as our main estimate, both because it is more comparable to the other frictions, and also because translating psychological switching costs from the Danish to the US setting is not obvious. Second, this set of simulations assumes an i.i.d. friction across the years, as opposed to assuming (as for other behavioral frictions) a fixed fraction of households with a persistent friction. Third, we assume that households refinance to a new 30-year mortgage; some households may instead decide to pay back the mortgage or take a shorter-duration one. We do not believe this has a first-order impact on the estimates.

### 2.3.2 Not Getting an Additional Mortgage Quote

While refinancing mortgages optimally is an important financial literacy skill, shopping to obtain the lowest rate is also a relevant dimension. Bhutta et al. (2026) uses a data set covering 30 percent of US mortgages and doc-

[18] In any one year, the loss variable is typically zero or positive. It can also be negative; for example, when the household is making payments later in their life due to refinancing to a new 30-year mortgage, whereas the mortgage would've already been paid back if they had not refinanced.

uments substantial dispersion in rates among loans given to observably similar borrowers. Despite this dispersion, only half of borrowers consider more than one lender, and only a few percent consider more than three lenders.

We measure the share $S_j$ at risk as the share with a house and a mortgage. To measure the share with a friction, we leverage data from Bhutta et al. (2026) which, based on a simple search model, provides estimates of the expected amount by which borrowers could reduce their rate if they were to obtain one additional rate quote. We consider it a friction to forego an expected interest rate reduction of more than 10 basis points. By this measure, 60 percent of low-income borrowers are at friction, compared to 47 percent of high-income borrowers. In estimating the loss $L_j$, we use the distribution of the basis point loss, conditional on that being higher than 10 basis points.

Importantly, one reason borrowers may not search for additional quotes is that they anticipate a rejection. Agarwal et al. (2024) show that the search cost is overstated by ignoring the possibility of rejection. To account for this, we estimate the share of mortgage applicants whose application is rejected by the lender, using the 2014 HMDA loan-application universe. We then assume that these applicants would have realized no loss from foregoing an additional quote because their application would have been denied; see subsection G.2 for additional details.

Table 3 shows an estimated loss $L_j$ of \$143 for low-income borrowers. To benchmark the magnitude, for low-income borrowers the average gain from an extra quote for the share with friction is 31 basis points, and a 30 percent probability of denial, which we apply to an average mortgage size of about \$120k. We conclude that, while this friction is non-negligible, it is 3-4 times smaller in impact compared to mortgage refinancing.

#### 2.3.3 Suboptimally Repaying Credit Card Debt

Credit card borrowing is very common in the United States, e.g., Lee and Maxted (2023). We focus on whether individuals with a credit card balance on at least two credit cards repay first the card with higher interest rate.

Figure C1f shows that the share of households in the SCF with at least two credit cards with balance is highest in the middle income group, peaking at nearly 40 percent. The plot also reports the average credit card balance for that group, with adjustment factors to compensate for the under-reporting of credit card borrowing in the SCF (Zinman, 2009; Beshears et al., 2018b).[19]

For individuals with multiple credit cards, the decision to repay should follow a simple rule: any repayment beyond the minimum required should go to the card with the higher interest rate. Yet, as Ponce et al. (2017) document using data from Mexico and as Gathergood et al. (2019) show using data from the UK, borrowers tend to repay cards equally, or repay the card with the smaller balance. Overall, only about 52 percent of repayment goes to the card with higher balance. To compute the share of individuals with the friction, we use the key finding in Gathergood et al. (2019) that only 10 percent of individuals put 100 percent of their credit card payment (in excess of the minimum), while 85 percent should be doing so. Thus we compute a rate with friction of $F_j = 1 - (.1/.85) = 0.88$. While Gathergood et al. (2019) does not present a break down by income, the incidence of the behavioral friction

[19] We take the adjustment factors specified by Beshears et al. (2018b) in Appendix C, namely multiplying the reported credit card balance by 1.8 in 2013, 1.5 in 2016, and 1.6 in 2019.

is very similar across dimensions such as the total payment, the interest rate difference, or how long individuals have had a card. We thus assume a constant friction $F_j$ across income groups.

To measure the loss $L_j$, we use the calculations in Tables 1 and 2 in Gathergood et al. (2019) of the annualized interest savings from a counterfactual of maximizing the repayment to the high-interest rate card, relative to the observed repayment. We rescale these savings by the average credit card balance in the SCF. Extrapolating from the UK context in Gathergood et al. (2019) to the US context seems reasonable given that both the amount of borrowing and the interest rates are comparable, with further details in subsection G.3.

**Notes and Caveats.** An important question is whether the repayment pattern represents a behavioral friction or some form of optimal decision-making. In this regard, a survey of credit card borrowers in Ponce et al. (2017) indicates that over 60 percent do not compare the interest rate of cards, and both papers point to a (suboptimal) balance matching heuristic as the most likely explanation. A caveat to our calculations is that the SCF data on credit card borrowing understates credit card borrowing. We compensate for this with an adjustment factor for the amount of debt, but we do not adjust the share of people who say they borrow on 2 or more credit cards.

#### 2.3.4 Paying Late Fees

A credit card late fee is a penalty charged by a credit card issuer to a cardholder when they fail to make at least their minimum payment by the statement due date. A late fee typically averages $30-$32.

We estimate the share with a credit card $S_j$ as well as the share $F_j$ of cardholders paying a late fee in the last 12 months using the publicly-available survey data from the 2023, 2024, and 2025 Making Ends Meet survey from the CFPB (CFPB, 2024b). Given that survey responses may not correctly report the extent of credit card usage or borrowing, we scale these estimates using administrative data from CFPB (2021, 2023, 2024a). Figure C1g displays the estimate for $S_j$ and $F_j$.

To estimate the average loss $L_j$ conditional on paying a late fee, we need an estimate of the average amount paid in late fees per year (conditional on at least one such fee). The 2021 Consumer Credit Card Market Report (CFPB, 2021) estimates that in 2020, i) the average credit card late fee was $31, ii) there were approximately 0.75 late fees per year per credit card account, and iii) there were, on average, 3.867 credit cards per cardholder. We combine these three estimates to determine that the average cardholder pays $\$31 * 0.75 * 3.867 = \$89.91$ in late fees per year. Given that only 23.26% of credit card holders pay any late fees per our survey data, we estimate that the credit card holders who pay any late fee pay $386.59 on average. Lacking additional information, this number is assumed to be constant across the income groups. This calculation likely understates the losses due to companies charging interest on late fees (which is especially relevant for low-income borrowers facing a higher APR).

#### 2.3.5 Paying Overdraft Fees

An overdraft fee is a penalty charged by a financial institution for a transaction greater than available funds when the financial institution covers the transaction.

Using the 2023, 2024, and 2025 CFPB Making Ends Meet surveys (CFPB, 2024b), we compute the share $S_j$ with

a checking or savings account, which is over 90 percent for the high-income groups, and over 70 percent for the low-income group (Figure C1h). The surveys indicate that among the people with an account, 23.95% have paid an overdraft fee in the past year. The administrative data from Low et al. (2017) indicates that the corresponding number should be 34%, so we scale our survey estimates of $F_j$ by a factor of 34/23.95. As Figure C1h shows, the share paying an overdraft fee is largest in the low-income group.

The annual loss $L_j$ is the average overdraft fee, \$35, times the number of overdrafts. As per our CFPB survey data, conditional on overdrafting at least once, the average person overdrafts 5.793 times in a year, which we rescale by 8.480/5.793 given the numbers in the administrative data in Low et al. (2017).

As Table 3 shows, the expected loss from overdraft fees is highest for the low-income group, \$110, with a smaller loss, \$44, for the high-income group. Other sources similarly estimate larger losses due to overdraft fees for low-income individuals, e.g., the New York Fed's 2023 Survey of Consumer Expectations (Leonard et al., 2025).

## 2.4 Insurance Frictions

### 2.4.1 Choosing Dominated Health Insurance

We define a dominated health insurance plan as a plan whose total cost is weakly higher at every level of medical spending than some alternative plan offered in the same menu. We focus on the active choice of dominated plans, as opposed to the choice of dominated plans due to changes in plan features and inertia, as in Handel (2013).[20]

First, we estimate the share of individuals $S_j$ offered a health insurance plan which includes a dominated option. We use the 2013-2019 waves of the Survey of Consumer Finances (SCF) to estimate first the share in each income group with a health insurance plan through the employer. Since we do not have micro-level evidence on the share of plans with a dominated option, we follow Liu and Sydnor (2022) which documents that 37% of firms in their sample include one strictly dominated plan[21] and define $S_j$ as the share with a health insurance plan times 0.37. As Figure C1i shows, this share is much higher for the high-income group than for the low-income group.

To estimate the likelihood $F_j$ that a worker enrolls in a dominated plan by employee income, we use data from Bhargava et al. (2017), which documents the health insurance choice in a company that offers a dominated plan and how it varies by income (Figure III Panel A). (Liu and Sydnor (2022) does not have evidence on the incidence of dominated choice by employee income.) Additional evidence that this friction is higher for low-income workers comes from Leive et al. (2025), documenting employee choice at a US university, and Rasmussen and Anderson (2021), with administrative data in the Netherlands. As far as the average share with the friction, the rate choosing the dominated plan in Liu and Sydnor (2022) is 53%, which is very similar to the 55% in Bhargava et al. (2017).

Finally, we compute the annual loss $L_j$ from the friction. Four estimates are Bhargava et al. (2017) (\$323), Liu and Sydnor (2022) (\$1,121), Leive et al. (2025) (\$1,700) and Rasmussen and Anderson (2021) (\$466). We use Liu and Sydnor (2022), which is the closest to a representative sample since it covers dozens of US companies.

**Notes and Caveats.** First, while Liu and Sydnor (2022) provide information on the proportion of *employers*

[20] For the latter phenomenon, we are not able to locate evidence on how common it is, and its share across income groups.
[21] Liu and Sydnor (2022) restrict their analysis sample to firms that offer one High-Deductible plan and one Low-Deductible plan.

who offer a dominated insurance plan, we extrapolate their findings to the proportion of *individuals* when we calculate $S$. Partly justifying this, Liu and Sydnor (2022) find few differences in the rate of dominated deductible plans across splits by characteristics such as firm size, industry, or employee salaries. Second, for households with borrowing constraints, the high-deductible plans can present a higher difficulty paying compared to the payment of predictably higher premium for the low-deductible plans (Ericson and Sydnor, 2018).

### 2.4.2 Suboptimally Lapsing Life Insurance

We identify life-insurance lapsing as a friction based, among others, on Gottlieb and Smetters (2021) and Ellis and Jaspersen (2025). Specifically, individuals on a term life insurance policy (TLI) – typically a 10- or 20-year policy – pay a constant premium over time for coverage in case they die within the time interval. Given that mortality is rising over the duration of the policy, individuals that lapse (that is, stop paying the premium) early on in the policy, and thus lose coverage, could have saved money by taking a shorter-duration TLI (with a lower premium). Gottlieb and Smetters (2021) document the role of naivete' in lapsing – the actual lapsing rate is several times larger than the anticipated lapsing rate, hence our coding as a behavioral friction.

Using the Survey of Consumer Finances (SCF), in Figure C1j we plot the share of individuals with a long-duration TLI, as well as a representative policy face value, as described in subsection H.2. Life insurance holdings peak at the age of 40-50, and are higher for high income individuals (as in Gropper and Kuhnen (2025)).

To impute the TLI purchases from the cross-sectional holdings, as well as the share of people lapsing, we use the rate of lapsing in panel B of Figure H1, which is quite substantial in the first 2 years of a TLI policy, especially for policies with lower coverage.

We consider lapsing within the first 10 years of their policy (i.e., those who lapse between the blue and yellow dots in Figure H2) to be suboptimal. These individuals could have purchased a 10-year policy instead, saving on their premiums. We define $S_j$ as the proportion who purchases long-duration TLIs, or the blue dots, while $F_j$ corresponds to the share of these individuals who are lapsers in the first 10 years (i.e., before the yellow dot).

We compute the average yearly saving $L_j$ early lapsers could have enjoyed by purchasing a 10-year policy instead of a 20-year policy. Using Compulife (2013) data, we estimate that the 10-year policy is 15-25 log points cheaper than a corresponding 20-year policy, with a larger difference at older ages (since the mortality increase becomes steeper). (Figure H3). We estimate the average annual savings for early lapsers across all years in which they overpay for their policy, as displayed in Table H1.

Table 3 summarizes the findings. The share with a friction is somewhat larger with low-income individuals, at 0.181, as opposed to 0.157 for high-income individuals. The share with a life insurance is much higher for high-income individuals, as in Gropper and Kuhnen (2025), as is the loss, given the higher life insurance coverage.

**Notes and Caveats.** Regarding the loss measure, an alternative measure is the benefit of reselling the life insurance on the secondary market, which likely would yield larger estimated losses. We did not pursue this route because the secondary market for TLI is very thin. Second, we acknowledge that not all the lapsing is necessarily a behavioral friction, but based on Gottlieb and Smetters (2021) we take it that the large majority is. Finally, our

estimates of lapsing rate depend on the income group only to the extent that they vary across the average policy size, as captured in Figure H1. The evidence from Ellis and Jaspersen (2025) on lapsing by wealth suggests that our measure understates the lapsing rates for low-income consumers.

## 2.5 Benefits Frictions

### 2.5.1 Not Claiming EITC Benefits

We identify as a behavioral friction the failure to claim EITC benefits for individuals that are eligible.

Figure I1 plots EITC eligibility and benefit level across marital status and number of children as of 2020. Using data from the 2011-2019 waves of the PSID, we estimate the share eligible $S_j$ as well as the average amount of money that they are eligible for, and which therefore they would lose were they not to claim ($L_j$), as function of the (permanent) income group. Regarding the friction, $F_j$, the evidence of an individual claiming rate of 80% and a dollar participation rate of 85% (Coleman et al., 2024) implies that the non-claiming rate is higher for lower benefit amounts. In light of this, we assume that individuals with a friction claim when benefits are above a threshold and do not claim otherwise, which allows us to estimate, shown in subsection I.1, a friction $F_j = 0.212$. Table 3 shows that the low income group has an average eligibility of 0.394, for an average loss of $978. For the middle-income group the eligibility numbers are much smaller and essentially zero for the high-income group, as expected.

Table I1 reconstructs Table 3 using our model implementation. Since our modeling approach involves averaging across married and unmarried households with and without kids, with more detail provided in subsection I.1, the proportion eligible ($S_j$) is significantly overstated in our model. To counteract that, the loss $L_j$ is lower in our model. The overall expected loss ($S_j * F_j * L_j$) in the model matches reasonably well the data, relatively close for the middle- and high-income groups and about 20 percent smaller for the low-income group.

**Notes and Caveats.** The amount of EITC we model reflects an average across households of different sizes and type. While this amount does not capture the heterogeneity of payments, it does capture the average payment. A second caveat is that we assume claiming and non-claiming households are similar within an income group, other than the behavioral friction. In reality, people who do not claim may have higher, or lower, consumption and income (e.g., Rafkin et al., 2023).

### 2.5.2 Not Claiming SNAP Benefits

We identify as a behavioral friction the failure to claim SNAP benefits for individuals that are eligible.

We model SNAP eligibility using data from the 2011-2019 waves of the PSID, applying the SNAP rules summarized in subsection I.2.[22] We estimate the share eligible $S_j$ as well as the average amount they are eligible for as function of the (permanent) income group. Estimating the share that does not claim $F_j$ is more difficult. On the one hand, the evidence from USDA tabulations in Vigil (2022) implies that the SNAP claiming rate is near 100% for individuals under the Federal Poverty Line (FPL) but only 42% for individuals above the FPL. On the other hand, the

[22] While the PSID also records the self-reported SNAP status, this variable is a notoriously noisy proxy of SNAP receipt, so we instead compute receipt ourselves based on the determining variables.

evidence from the PSID is that the SNAP claiming rate is 54% for individuals under the FPL and 42% for individuals above the FPL. The large discrepancy in part is due to the difficulty of measuring the census of eligible individuals. We take an average of these two estimates, assuming that the claiming rate is 76% for individuals under the FPL and 42% for individuals over the FPL. To match these numbers, we assume that the share at friction is $F_j = .58$, and those individuals claim when they are below the FPL, and claim a share of the available SNAP equal to $\frac{0.76-0.42}{1.00-0.42}$ when they are above the FPL. Table 3 shows that the low-income group has an average eligibility of 0.394 for an average loss of $253. For the middle-income and low-income group the eligibility numbers are much smaller.

Table I3 reconstructs Table 3 using our model implementation. Since our modeling approach involves averaging across married and unmarried households with and without kids, the proportion eligible ($S_j$) is higher in our model. Counteracting that, the average loss due to not claiming ($L_j$) is lower. Overall, we match the expected loss ($S_j * F_j * L_j$) quite well, though we understate the loss for the middle- and high-income households.

**Notes and Caveats.** Similar caveats to the ones for EITC apply. For example, the non-claimants of SNAP may differ systematically from claimants in ways other than how we model it.[23]

## 2.6 Health Frictions

### 2.6.1 Not Taking Statin Medications

Nearly two-thirds of the US population have at least one risk factor for cardiovascular disease (Fryar et al., 2024), and deaths due to cardiovascular disease are a significant fraction of all deaths, as Figure J1 shows using CDC data. Statins are highly effective in mitigating the risk of cardiovascular disease, yet, their take up is far from 100 percent. We model the failure to take statins when prescribed as a friction and model its impact on mortality.

First, we compute the share $S_j$ of individuals who meet guidelines for statin using the question in the 2010-19 NHIS whether respondents have had high cholesterol within the past 12 months. Figure C1k shows that this share increases with age up to 60 percent at age 70 and is quite similar across the income groups.

To measure $F_j$, the share of those who should take statins that fail to do so, we use Verma et al. (2017) that calculates this share using NHANES data from 2005-2012 by income quartile in Table 3. The share that fails to take statins is strikingly large, 47 percent in the low-income group and 36 percent in the high-income group.

To measure the cost $L_j$ of failing to take statins, we consider a half dozen RCTs on the effectiveness of statins run in the 1990s. The typical study randomizes individuals into a statin arm or a placebo arm with an intent-to-treat design, that is, some individuals in the treatment group do not comply and conversely some individuals in the placebo group do get the statin. In some cases, both groups receive other medications for cardiovascular conditions (such as aspirin) so the estimated effect of the statin is on top of the effectiveness of other medications. When studies report the first stage, we compute the treatment-on-the-treated estimate.[24]

[23] Finkelstein and Notowidigdo (2019) provide some evidence from an RCT on non-claimants using various nudges to encourage them to claim. Compared to the control group, the group that claims in response to the nudges – i.e., the marginal claimants – are less needy, implying that lowering hurdles brings in less needy individuals. At the same time, though, the group that does not claim even with the nudges is needier.

[24] For example, if 87 percent of people in the treatment group and 12 percent of people in the placebo group take statins, we boost the ITT estimate (which is the one that studies report as main result) by $1/(87-12)$.

We summarize the results of 8 key studies (Sever et al., 2003; Heart Protection Study Collaborative Group, 2002; Downs et al., 1998; Shepherd et al., 1995; Ridker et al., 2008; Sacks, 1996; Scandinavian Simvastatin Survival Study Group, 1994; The LIPID Study Group, 1998) reporting (i) the ITT impact on percent reduction on cardiovascular events, with confidence intervals, (ii) the implied TOT effect when available, (iii) the impact on cardiovascular mortality, ITT and (iv) the impact on cardiovascular mortality, TOT. Table J1 summarizes our results. If there is no estimate of the first-stage, we report the TOT estimate as equal to the ITT.

On average, failing to take statins increases the cardiovascular mortality by 26.5% (s.e. 3.1%). In this population, cardiovascular deaths account for 56.9 percent of all deaths, as computed averaging over the studies above. Thus, failing to stake statins increases overall mortality by 15.1% (s.e. = 1.7%). In the counterfactual that removes the frictions, we lower the mortality by this percent for the population with the friction. We also add an annual cost of statins of $96 for the share that is uninsured, as detailed in subsection J.1. Table 3 summarizes the findings.

**Notes and Caveats.** We model the impact of failing to take statins on mortality and do not account for its impact on labor market participation, disability and earnings. Also, as our estimate of the impact of statins, we use the impact from RCTs on mortality, not on cardiovascular episodes, which would yield a larger estimate.

### 2.6.2 Not Screening for Colon Cancer

Among the causes for preventable deaths, colorectal cancer (CRC) is first-order. As Figure J2 shows, CRC deaths are about 3 percent of deaths among 50-59 year olds and about 1.5 percent among older people. We summarize below evidence from RCTs indicating that screening reduces the mortality from CRC. We code lack of screening as a friction leading to a higher mortality rate. We envision this as an example of how regular health screening can impact life-cycle outcomes. In the final section, we discuss partial evidence on other preventative health behaviors.

The original evidence comes from an RCT (Mandel et al., 1993) with 46,000 participants showing a 33 percent (s.e. = 9 percent) reduction in CRC-specific mortality (measured 13 years out) from annual fecal occult blood testing. This testing is relatively low cost and the effectiveness with the recent testing should plausibly be higher.

A more recent set of RCTs (Shroff et al., 2014) examine the effectiveness of screening using flexible sigmoidoscopy which is a lower-cost (and lower hassle) procedure compared to a colonoscopy given that it covers about half of the colon. The results are from 4 prospective RCTs for flexible sigmoidoscopy and show, pooled across the 4 sites, a reduction in the CRC-specific mortality of 28 percent (s.e. = 4 percent).

One RCT trial (Bretthauer et al., 2022) evaluates the effectiveness of colonoscopies, which are the full (and more costly and invasive) testing for CRC. The paper finds a 10 percent (not statistically significant) reduction in CRC mortality 10 years out. A limitation of this study is that compliance in the group invited to have a colonoscopy is only 42 percent, so the authors cannot rule out potentially large reductions in mortality.

We assume that skipping the lower-nuisance screening (the fecal testing or the sigmoidoscopy) is a behavioral friction. Using the inverse-variance weighted average of the two studies, we assume that CRC screening reduces CRC mortality by 28.8 percent (s.e. = 3.7), a percent reduction which we assume to be constant for all ages above 50 (as screening is not recommended below 50). We assume no reduction on other sources of mortality.

In the counterfactual in which we remove the friction, we reduce the CRC mortality for the individuals with friction by 28.8 percent, and assume a cost of the screening for the share uninsured, as detailed in subsection J.2.

Our measure of $F_j$ is the share aged above 50 that has not undertaken a CRC screening in the last 5 years, using NHIS data: 62 percent for the low-income group and 44 percent for the high-income group (Table 3). The share at risk, $S_{jt}$, is zero below age 50 (the recommended screening age) and one above it.

While this section focuses entirely on one preventative health behavior given the difficulty of obtaining RCT-based evidence on the impacts of health behaviors, we document the rate at which individuals undertake preventative health behaviors using the NHIS data. Table J5 documents the share that has not had a flu shot in the past year (for individuals above age 65), that has not done breast cancer screening in the past 2 years (for women above 50), and that has not done cervical cancer screening in the past 3 years (for all women). The share for all three is sizable and is, in all three cases, higher for the low-income group, echoing the findings for the CRC prevention.

**Notes and Caveats.** We assume that skipping the CRC screening is a behavioral friction. While colonoscopies are a significant nuisance (typically a day or fasting and a day-long bowel prep), fecal testing and sigmoidoscopies are significantly lower annoyance. Another caveat is that the estimates do not include any economic impact of the higher incidence of colorectal cancer, such as lower labor force participation, losses in earnings and disability.

#### 2.6.3 Failing to Quit Smoking

This behavioral friction is continuing to smoke despite wanting to quit. We consider it a friction in light of a self-control problem, though we acknowledge that it could be interpreted in light of a rational addiction model.

We estimate the share of smokers who intend to quit using data from the NHIS. The NHIS is a cross-sectional dataset but it has detailed information on current smoking status, intent to quit, and, for former smokers, when they last smoked. As Figure J3 shows, the share of smokers is significantly higher for the low-income group, peaking around age 50 at 35 percent; it peaks in the early 20s for the high- and middle-income groups, and at significantly lower levels. The share of smokers that intend to quit is about constant at about 70 percent (Figure J4).

We aim to measure the behavioral friction $F_j$ as the share of individuals who want to quit, but do not manage and continue smoking. In providing such measure, there are two main difficulties. First, continuing to smoke versus quitting has different health implications whether one stops at age 25 versus at age 60; the cumulative damage due to smoking is much more serious in the latter case and thus the benefits of stopping smaller. Second, it is common for smokers to quit and re-start; we thus need to set a threshold to count successful quitting.

On the first issue, we use NHIS mortality data to estimate the difference in mortality at different ages (from age 60 onwards) depending on whether an individual is a current smoker, a never smoker, or a former smoker who stopped smoking in a particular age range. As Figure J5 shows, the mortality rate of non-smokers is about one third that of smokers. Interestingly, former smokers who quit by age 50 have a quite similar mortality rate as non-smokers. In contrast, former smokers who quit after age 50 have a mortality rate closer to the one of smokers.

Based on this evidence, we designate age 50 as a critical age for quitting. We take as the relevant population both the current smokers at age 50 who would like to quit, as well as individuals who are former smokers as of age

50; to ensure that quitting is a permanent, rather than temporary, status, we measure quitting by age 50 at the age of 53. We then compute the share of this population that is a current smoker at age 50 despite wanting to quit.

We measure the mortality loss due to smoking $L_j$ by comparing the mortality of continuing smokers past age 50 to the mortality of smokers who quit before age 50 or of those who never smoke. Using the evidence in Figure J5, we estimate that failing to quit increases the mortality by a factor of 2.37 for age 50-74 and by 1.90 for ages 75+. (The latter factor is smaller given that mortality is much higher at older ages, which moderates the extent to which smoking can increase it.) The mortality impact of smoking is similar to estimates in prior studies (Doll et al., 2004; Pirie et al., 2013; Jha, 2020; Foote et al., 2025), amounting to a shorter life expectancy at 50 by 6.7 years. The second loss due to smoking is the cost of purchasing cigarettes, which we estimate using the average number of cigarettes smoked, 13 per day, times the average cost per cigarette in 2014, 30 cents.

As summarized in Table J4, the share at risk $S_j$ incudes smokers as of age 50 who want to quit and former smokers who stopped before age 50 (since by definition former smokers are smokers who wanted to quit). The share with friction $F_j$ is the share of the above group that still smokes at age 50. The loss $L_j$ is the sum of the mortality cost and the cigarette expenditure cost.

**Notes and Caveats.** We interpret smoking as a self-control friction: an individual would like future selves to stop smoking, but not at present, thus the focus on smokers that aim to quit. Observational evidence from Gruber and Köszegi (2001) and demand for commitment devices to stop smoking in Giné et al. (2010) suggest this interpretation is plausible. Under the alternative interpretation as rational addiction (Becker and Murphy, 1988), our estimates represent the impact of an optimizing ex ante choice. An additional caveat is that we do not account for the loss of employment due to disability or, on the other side, for the hedonic benefits of smoking.

## 2.7 Correlations

So far, we have estimated each friction individually. An important question is whether the frictions are correlated, within an income group. While such correlation does not affect our estimate of $S_j \cdot F_j \cdot L_j$, it influences our implementation of the frictions in the model. We thus provide evidence in this section on correlation in the friction indicator, that is, whether individuals that have a friction are also more likely to have another friction.[25]

While we do not have systematic evidence across all frictions, we are able to measure the correlation across several pairs of frictions: (i) not investing in stock funds, saving in low interest accounts, and under-diversification, using SCF data; (ii) paying late fees and paying overdraft fees, using CFPB data; (iii) choosing dominated insurance plans and not meeting the employer 401(k) match, using data from Leive et al. (2025); (iv) failing to quit smoking and not screening for colon cancer, using NHIS data. For each of these pairs of outcomes, we estimate a bi-variate probit in which the dependent variables are the two binary friction indicators and the only regressors are indicators for the three permanent income groups. The bi-variate probit assumes that each friction indicator is driven by a latent normal variable crossing a threshold, with the two latent variables distributed jointly normal. The estimated

[25] One could also examine correlation in the share at risk $S_j$ or the loss $L_j$. We do not consider such correlations, because they are not random variables in our model.

correlation between these two latent variables — the tetrachoric correlation — measures the within-income-group correlation between the two frictions. As Table 4 shows, the correlation varies from -0.238 to 0.670, with an average of 0.032 (s.e. = 0.006). While Stango and Zinman (2023) measure biases rather than frictions, the correlation we estimate is close to their estimate of 0.13. In the model, we use the late-fee/overdraft correlation when combining those two fees into one friction; all off-diagonal friction correlations are set to zero in the current draft.

# 3 Summarizing the Effects of Frictions

We summarize the impact of each friction with the key summary statistics $S_j$, $F_j$, and $L_j$. In particular, we focus on the product $S_j \cdot F_j \cdot L_j$, which is the average annual per-person loss from the friction for that income group.

Before we present the relevant figures, we stress a number of caveats. First, the estimates are based on a combination of data sources, including survey responses, findings from the literature, and model simulations. While we aim to capture uncertainty in the estimates with the confidence intervals, these intervals do not account for additional model uncertainty and subjective decisions that influence the final estimate. Second, the estimates collapse different types of losses into a single variable – in some cases, the losses are due to foregone employer match; in other cases, they reflect increased spending; in other cases still, increased mortality. It is important to keep such differences in mind. Third, while we interpret all of these choices as frictions, we acknowledge that not everyone will agree. In this case, these estimates can be interpreted as lower bounds on the (monetary or utility) costs that are required to rationalize choices within each income group.

## 3.1 Comparison Across Frictions and Aggregation

Panel A of Figure 1 shows, for each friction, the unconditional loss, $\Delta_j$, for the low-income group (x-axis) and the high-income group (y-axis). The results show that some frictions have larger losses among low-income earners, such as not claiming government benefits and smoking, while others have larger effects for high income earners, such as paying excessive mutual fund fees and under-diversification.

Panel B reproduces Panel A using the unconditional losses as a percentage of the average consumable income within the income group, $\Delta_j / \overline{R}_j$. We compute $\overline{R}_j$ by summing the components in (3) using the 2011-2019 PSID, which results in $22,000 for the low-income group and $91,000 for the high-income group; see Appendix B for additional details. These results show the losses are generally larger for low-income individuals in percentage terms. Specifically, 9 frictions affect the average income of low-earners by at least 0.4% of their annual income, while only 4 frictions affect the high-income group by more than 0.4% of income.

An important exception to this pattern are the savings frictions, which have larger percentage losses for higher-income individuals. This is because the losses from savings frictions are proportional to wealth, and wealth is more unequally distributed than income. Interestingly, these savings frictions are the ones most commonly featured in financial literacy syllabi at top universities. Thus, if one were to evaluate the impact of behavioral frictions featured in such syllabi, one would conclude that its incidence is larger on high-income people, even in percent term. While

this is correct for those frictions, it is not true for all the other categories of frictions we consider. This suggests that it is important to consider the different categories of frictions, as we aim to do in this paper.

As an approximate measure of the overall impact of the frictions, we take the sum across frictions of their impact (as fraction of consumable income). The sum is designed to be a conservative estimate of the impact of turning off the frictions, as it does not take into account interactions between frictions, which are generally positive. For example, higher college attendance (implied by removing the education frictions) raises the value of longer life expectancy (implied by removing the health frictions). Similarly, lowering the mutual fund fees increases the return to participating in the stock market, which instead is currently computed at the average level of fees.

While we do not take into account interactions between frictions, we avoid explicit double-counting in potential savings. This is only relevant for one pair of frictions: individuals who invest in individual stocks but not in stock funds. For this pair of frictions, it is often not possible to alleviate both frictions simultaneously (i.e., when someone has >50% of their wealth in individual stocks, alleviating both frictions requires them to move the same individual stock wealth to stock funds instead). Thus we only consider the savings from alleviating the individual stocks friction. Accounting for this, the combined $S_j \cdot F_j \cdot L_j$ for both frictions drops from \$83 to \$78 for low-income individuals, \$221 to \$208 for middle-income individuals, and \$439 to \$428 for high-income individuals.

Summing across the 19 frictions, we estimate annual losses of 8.23% for the low-income group, 4.98% for the middle-income group, and 2.96% for the high-income group. Thus, the losses are sizable across groups, but they loom especially large for the low-income group. Two frictions are quantitatively especially important in this respect – failing to quit smoking and failing to claim SNAP. Even if we exclude these two frictions, however, the frictions on average affect the low-income group more than the other groups.

### 3.2 Benchmarking the Losses from Frictions

As a first way to assess the magnitude of the total losses due to frictions, we compare them against the earnings impact of two policies: all states implementing an EITC equal to 25% of the federal EITC, and the government switching the 2020 tax code to the 2016 tax code (thus reverting the Tax Cuts and Jobs Act of 2017). Regarding the first policy, in 2025, 20 states offered an EITC supplement equivalent to a set percentage of the federal EITC level, with the median (mean) supplement equal to 22.5% (25.8%) of the federal EITC. We assume a hypothetical policy change where all states offer an EITC supplement equivalent to 25% of the federal EITC, assuming no change in the likelihood of EITC claiming (i.e., $F_j$). The additional EITC supplement would lead for the low-income group to a gain of 0.72% of annual income on average. The impact of this major anti-poverty policy is only approximately twice as large as the impact of an average behavioral friction for low-income consumers.

The second policy is a reversion to the 2016 tax code. The Tax Cuts and Jobs Act of 2017 reduced taxes, increasing the standard deduction for individuals from \$6,350 to \$12,000 and decreasing the top marginal tax rate from 39.6% to 37.0%. We compute the mechanical effects of undoing this tax reform, assuming no behavioral responses. Per Figure 1, the high-income group would lose 4.13% of their post-tax income (and the low-income group 1.25% of their post-tax income). Thus, this reform has a larger effect on high-earners' income than any individual high-

income friction, but a smaller effect than the sum of all high-income behavioral frictions.

This comparison to outside policies thus confirms the different magnitude of the behavioral frictions for low- versus high-income consumers. The losses to low-income consumers from the sum of the behavioral frictions are approximately 8.5 times larger than the impact of the EITC reform. In contrast, the losses to high-income consumers from the sum of the behavioral frictions are larger than the gain associated with one major tax reform, although the tax reform remains larger than any individual high-income friction.

As a complementary way to assess the magnitude of the losses, we compare them to the annual consumption on two major categories, food expenditure and utilities expenditure, using PSID data. Low-income consumers spend 23.8% (S.E. 0.15%) of the annual consumable income on food and 9.7% (S.E. 0.07%) on utilities. Thus, the total estimated losses are actually larger than the amount spent annually on utilities. In comparison, high-income consumers spend 8.9% (S.E. 0.05%) of the annual consumable income on food and 2.6% (S.E. 0.02%) on utilities. For them as well, the losses due to friction are slightly larger than their utility consumption.

### 3.3 Comparison of Friction Impact with Expert Forecasts

### 3.4 Coverage of Frictions In Syllabi, Literature, and Press

Given the measure of the impact of the frictions for the low-income and high-income groups, an important question is what predicts the extent to which such frictions are covered in the literature. Are the frictions with the largest impact for high-income consumers more covered? Or the ones with more impact on low-income consumers? Or is the coverage orthogonal to the measure of losses?

We present two different measures of coverage in the literature. The first one is the inclusion in syllabi as used in Table 1, both the ones from top universities, and the one in high-school curricula across the country. Our coding of these syllabi is described in Appendix A. The second measure counts instead the number of papers dedicated to each topic, as published in one of the traditional top-5 journals in economics or in one of the AEJ journals, from 2000 until 2025. We count the number of articles using a set of keywords run on the abstract and title of all the articles, and build both a narrower measure (e.g. papers on failure to invest in 401(k)s) and a broader measure (e.g., papers on investing in 401(k)s).

Table * presents regressions of the count of coverage in syllabi (Columns 1 and 2) and number of articles in the literature with a narrow measure (Column 3) and a broad measure (Column 4). The regressors are the estimated percent loss for the low-income group and for the high-income group. We find ***.

### 3.5 Decomposing the Losses from Frictions

A key advantage of our framework is that we can decompose the losses from each friction, $S_j \cdot F_j \cdot L_j$, into its components. Figure 2 shows scatterplots similar to Figure 1 in which we separately plot the share of at risk $S_j$, the share with a friction $F_j$, the dollar loss $L_j$ and the loss as percent of average income $L_j/Y_j$. We find that $S_j$ tends to be higher for the high-income groups and $L_j/Y_j$ is larger for the high-income group about half the time.

In contrast, $F_j$ is higher for the low-income group in nearly all cases where we have separate estimates for the two groups. This is important because it highlights that differences in losses from frictions across income groups are largely due to heterogeneity in the *incidence* of frictions.

Given the importance of friction incidence, Figure 3 shows the losses from a counterfactual in which we equate the prevalence of frictions in the low- and middle-income groups to match that of the high-income group rather than removing frictions for all individuals. In this case, the total gain for low-income individuals falls by around 40% to 9.6%, which is still comparable to their utility spending and larger than the effects of an EITC expansion. To the extent that the prevalence of the friction among high-income individuals represents the fraction of individuals for which these choices are actually optimizing choices, these estimates suggest that the losses from frictions are still quantitatively meaningful.

### 3.6 The Evolution of Frictions Over Time

Our baseline estimates measure the impact of behavioral frictions during the 2010s. An important question is whether some frictions have become more, or less, important over time. That can provide information on trends (in addition to levels) and also on the impact of certain policies. While we cannot track the evolution of all frictions, for 8 frictions – the education and savings frictions and the smoking friction – we measure the change over time in some of the key parameters $S_j$, $F_j$ and $L_j$. The change we measure is typically in $S_j$, but in some cases for other parameters as well. The two other time periods we consider are the 1990s and 2020s (whenever possible).

Figure 4 plots data from Table D1, showing how the average loss (as a percentage of income) varies over time. The points represent our baseline estimates; the incoming (outgoing) arrows start (end) at our estimate in the 1990s (2020s). A friction that has changed substantially over time is for-profit college attendance: between the 1990s and the 2010s, the losses increased due to higher attendance of for-profit colleges, but they then declined substantially in the 2020s, due to regulatory changes during the Obama presidency which made it more difficult for for-profit colleges to be certified. Another friction that has changed substantially is smoking. The losses for high-income people have declined from the 1990s to the 2010s due to a secular decline in the share of smokers. Interestingly, the losses for the low-income group have instead substantially increased over the same time period. As the decomposition in Table D1 shows, while the share of low-income smokers has slightly decreased, a stronger countervailing force is that the price of cigarettes has about doubled (in real terms), given the increase in tobacco taxation. In this case too, thus, the changes reflect changes in policy levers.

In other cases, the losses have changed due to a change in the financial position of households. For example, for high-income individuals the losses due to excess mutual fund fees have increased over time, despite the decline in mutual fund fees, and similarly for the losses from underdiversification and from the checking account friction. The main driver is the increase in household wealth, which is larger at the top of the distribution due to differences in portfolio composition (Greenwald et al., 2021). Conversely, the losses from stock market non-participation have decreased, due to the increase in participation enabled by the growth of low-fee index funds and easily-accessible brokerage accounts. Finally, the losses due to missing the 401(k) match have decreased over time for high-income

consumers, given the higher participation, while they stayed about constant for low-income consumers.

Overall, we hope that the approach we propose to measure the losses due to behavioral frictions can be used to track the impact of policies over time, as well as time trends, along the lines of what we documented here.

# 4 Life Cycle Model

This section describes our life cycle model, with additional details presented in Section K.1. The model is in partial equilibrium. There are several ingredients that we plan to incorporate into future versions of the model, including endogenous homeownership and medical expenses in retirement. Throughout, we denote $\mathbf{f}_i \in \{0,1\}^N$ as the friction vector, with $j$th element denoted by $f_i^j$. Each element of this vector is permanent: an individual's friction assignment is determined at birth and remains fixed throughout their life.[26] Individuals are fully aware of their friction vector and correctly account for it when making decisions. For now, the set of frictions that we incorporate into the model is a subset of the frictions described above, but in future versions of this draft we plan to incorporate all of the frictions. We assign frictions using the tetrachoric-correlation structure described below; in the current implementation, all off-diagonal correlations are set to zero.

## 4.1 Model Description

**Demographics and Education.** Time is discrete and each period lasts one year. Individuals are born at age $a_{it} = 0$ and assigned to one of $N_e$ education groups, $e_i \in \{1,\ldots,N_e\}$. Education determines the deterministic component of income, student debt, the initial distribution of liquid assets, the number of children, and the income process parameters. Individuals are in their working life while $a_{it} < a_R$, where they earn stochastic income. At $a_{it} \geq a_R$, individuals exogenously enter retirement and receive deterministic social security benefits. At age $a_{it} = a_T$, individuals die with certainty. Prior to $a_T$, individuals face mortality risk with survival probability $\mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i)$ that depends on age, permanent income group, and the friction vector. Each individual has a number of children that is a deterministic function of age and education, and the effective family size $n_{it}$ is computed using an equivalence scale.

**Income Process and Permanent Income Groups.** Individuals are in one of $N_\delta = 3$ permanent income groups, $\{\delta_j\}_{j=1}^{N_\delta}$, which determines many features of individuals' choice environment in the model, including the deterministic age profile, survival probabilities, 401(k) access, and the prevalence of frictions. Our model of the income process follows Braxton et al. (2025). Individual income $y_{it}$ depends on whether individuals are employed ($\zeta_{it} = E$) or unemployed ($\zeta_{it} = U$). When employed, log income is the sum of a group-specific intercept $\overline{y}(\delta_i, e_i)$, a deterministic age profile $f(a_{it}, e_i, \delta_i)$ that is a cubic polynomial in age, a persistent component $z_{it}$, and a transitory shock $\epsilon_{it}$ whose distribution varies by age and a two-bin education classification ($e_i = 4$ vs. $e_i \leq 3$), which is the

[26] Given a lack of data, we view perfect persistence as a natural starting point because of its computational benefits and because Stango and Zinman (forthcoming) find a high degree of persistence of biases, summarizing their results as "support[ing] macro models that are micro-founded on deep behavioral tendencies and/or assume fixed shares of behavioral and non-behavioral agents over time."

level at which the stochastic parameters of the income process are estimated in Braxton et al. (2025). When unemployed, individuals earn a fraction $\ell$ of their deterministic and persistent income, without a transitory shock. We impose an income floor of $\underline{y}$, and income is zero in retirement. Employment status $\zeta_{it}$ transitions stochastically, with the probability of unemployment depending on persistent income, current employment status, the same two-bin education classification, and frictions. The persistent component $z_{it}$ follows an AR(1) process whose persistence, drift, and innovation volatility depend on the two-bin education classification and current employment status, and is set at its last working-life value upon entering retirement.

**Savings and Portfolio Choice.** Individuals have access to a liquid account with balance $L_{it}$ and make liquid savings choices $S^L_{it}$. The liquid account balance evolves as follows:

$$L_{it} = \begin{cases} L_{i0} \sim F_L(\cdot \mid e_i) & \text{if } a_{it} = 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i))\left(R^f + \tau^0_L\right) & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) < 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i)) \cdot R^{\theta,\text{net}}_{it} & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) \geq 0 \end{cases} \tag{9}$$

where $F_L(\cdot \mid e_i)$ is the distribution of initial liquid assets, $R^f$ is the gross risk-free rate, $\tau^0_L$ is the interest rate spread on borrowing, $R^{\theta,\text{net}}_{it}$ is the after-tax portfolio return described below, and $\mathscr{L}_{it}(\mathbf{f}_i)$ denotes the total dollar loss from frictions described in Section 4.2. Liquid savings are subject to a borrowing limit that is proportional to the deterministic component of income during working life, is frozen at its last working-life value during retirement, and is zero at the terminal age. When saving, individuals earn an after-tax portfolio return that depends on a blended capital gains tax rate.

A subset of individuals have access to an illiquid account modeled after a 401(k), with access $I^X_i \in \{0,1\}$ drawn at birth from a Bernoulli distribution whose probability depends on permanent income group. Contributions $S^X_{it}$ can only be made when employed, are employer-matched at a rate $m_x$ up to a cap of $c_x$ as a fraction of income, and are subject to IRS contribution limits $\overline{x}(a_{it})$. Withdrawals are allowed freely in retirement but are subject to an early withdrawal penalty $\phi_x(a_{it})$ prior to a threshold age. While unemployed, remaining balances are partially vested each period. The illiquid account earns the pre-tax portfolio return $R^\theta_{it}$, since 401(k) accounts are tax-deferred. The balance in this account is denoted by $X_{it}$, so an individual's total wealth is $W_{it} = L_{it} + I^X_i \cdot X_{it}$.

Individuals can invest wealth within both accounts into a risk-free bond with return $R^f$ and a risky stock with equity premium $\mu_s$ and volatility $\sigma_{rs}$. They choose a portfolio share $\theta_{it} \in [0,1]$, with stock market participation incurring a per-period cost $\tau_p(\delta_i)$. For tractability, we restrict individuals to choosing the same portfolio allocation in both accounts. A subset of frictions affect portfolio choice decisions, which are described in Section 4.2.

**Transfers and Taxes.** Individuals receive several government transfers and pay income taxes. In retirement, individuals receive social security benefits that are a piecewise linear function of approximate average lifetime earnings. During working life, individuals receive Earned Income Tax Credit (EITC) benefits and Supplemental Nutrition Assistance Program (SNAP) benefits, each modeled as a polynomial approximation of the federal formula

with age-group-specific coefficients. SNAP benefits continue in retirement, with social security income used as the income basis. In retirement, individuals with wealth below a threshold have access to Supplemental Security Income (SSI). Individuals receive inheritances that are a deterministic function of age and education, and repay student debt over the first $T_d$ years of life according to a fixed repayment schedule with debt balance $D(e_i, \mathbf{f}_i)$ that depends on education group and the friction vector. Taxable income equals labor income (or social security benefits in retirement) minus 401(k) contributions, and income taxes $T_{it}^y = \mathcal{T}_y(y_{it}^T)$ are computed using a progressive tax schedule. The government ensures a consumption floor $\underline{c}$ via a transfer $T_{it}^{\text{floor}}$.

**Preferences.** Individuals have time-separable CRRA expected utility preferences with discount factor $\beta$ and coefficient of relative risk aversion $\gamma$, adjusted for family size using the equivalence scale $n_{it}$. When an individual saves positively and allocates a positive share to stocks, consumption is reduced by the per-period stock market participation cost $\tau_p(\delta_i)$. When individuals die, they receive utility from bequeathing their wealth, following De Nardi et al. (2010), with bequest strength parameter $\psi_1$ and luxury parameter $\psi_2$.

**Summary of Problem.** Individuals face a dynamic optimization problem with the following state variables: $a_{it}$ (age), $e_i$ (education), $\delta_i$ (permanent income group), $\zeta_{it}$ (employment status), $z_{it}$ (persistent income), $\epsilon_{it}$ (transitory income shock), $L_{it}$ (liquid account balance), $X_{it}$ (illiquid account balance), $I_i^X$ (401(k) access indicator), and $\mathbf{f}_i \in \{0,1\}^N$ (friction vector). Because the friction vector is fixed throughout an individual's life, it enters as a parameter of the value function rather than a state that evolves stochastically. Individuals make 3 choices: $S_{it}^L$ (liquid savings), $S_{it}^X$ (illiquid savings), and $\theta_{it}$ (portfolio share). Consumption is pinned down by the budget constraint. These choices are made subject to uncertainty about next period's states: $D_{it+1}$ (mortality), $\zeta_{it+1}$ (employment status), $\eta_{it+1}$ (persistent income innovation), $\epsilon_{it+1}$ (transitory income shock), and $\epsilon_{t+1}^s$ (stock return innovation). In retirement, the income process states $z_{it}$ and $\zeta_{it}$ are no longer stochastic (persistent income is frozen and employment is irrelevant); the relevant sources of uncertainty are mortality and stock return innovations. The recursive formulation of this problem is presented in Section K.2.

## 4.2 Frictions that Have Been Incorporated

The prevalence estimates $S$ and $F$ for each friction are reported in Table 3. Here we describe how each friction enters the model.

**Education Frictions.** The college attendance friction applies to individuals with $e_i = 1$ (no college). Those without this friction are treated as having attended college: they receive a log earnings gain added to the age profile after age 26, take on additional student debt, and pay an upfront cost that captures foregone earnings while attending college, split between a reduction in initial liquid assets and a reduction in first-period consumption using a marginal propensity to save of 0.6 (Kaplan and Violante, 2022). The for-profit attendance friction assigns a fraction of individuals in education group $e_i = 2$ to $e_i = 3$, which imposes a log earnings penalty on their age profile,

increases the probability of unemployment, and increases student debt, calibrated from the estimates of Cellini and Turner (2019).

**Not Investing in Stock Mutual Funds.** Individuals with this friction are forced to invest entirely in the risk-free bond, so $\theta_{it} = 0$ in all periods. The share at risk $S$ is the share of individuals with sufficient savings to invest in equity, and $F$ is calibrated such that the observed participation rate in the model matches the data, using estimates from Choukhmane and de Silva (2026) to pin down the counterfactual frictionless participation rate.

**Direct Dollar Loss Frictions.** The combined overdraft and late-fee friction and the dominated insurance choice friction are modeled as direct dollar losses subtracted from the liquid account each period. We combine overdraft fees and credit card late fees into one friction, using their assumed correlation in Table 4.[27] We do not incorporate the suboptimally lapsing life insurance friction into the model because its estimated losses are relatively small. For these frictions, Section 1 distinguishes individuals who are "at risk" of the loss (share $S_j$) from those who are not, and estimates the per-period dollar loss $L_j$ conditional on being at risk. Whereas Section 1 reports $L_j$ averaged over ages for summary purposes, we estimate it at each age so that the per-period loss can vary over the life cycle. In the model, we set the model's share at risk to one for every individual and absorb the empirical share $S_j$ into the loss itself, so that the per-period loss assigned to an individual with $f_i^j = 1$ is $\lambda_j(a_{it}, \delta_i) = S_j \cdot L_j(a_{it}, \delta_i)$.[28] The total dollar loss from these frictions in period $t$ is:

$$\mathscr{L}_{it}(\mathbf{f}_i) = \sum_{j \in \mathscr{J}} f_i^j \cdot \lambda_j(a_{it}, \delta_i) \tag{10}$$

where $\mathscr{J}$ contains the direct dollar-loss frictions and the health frictions' direct dollar-loss components described below. These dollar losses are subtracted from liquid savings before computing returns, as shown in (9).

**Benefit Claiming Frictions.** The EITC and SNAP claiming frictions reduce government transfers rather than entering as direct dollar losses. For EITC, individuals with the friction receive only the component of benefits predicted among households that always claim; removing the friction allows them to receive the larger of this amount and the broader EITC schedule estimated from households that sometimes claim. For SNAP, individuals with the friction receive no SNAP benefits when income exceeds the federal poverty line; removing the friction restores the polynomial benefit schedule estimated from PSID eligibility rules and claiming behavior.

**Mortality Frictions.** Two frictions — failing to take statins and smoking — affect mortality, scaling the death probability by multiplicative factors that can vary with age and income group. In addition, the model includes direct

[27] To combine the overdraft and late fees frictions into one friction, we take 2.5 million low-income, 5 million middle-income, and 2.5 million high-income draws from two bivariate normal distributions. The first distribution has correlation 0.488, corresponding to the estimated tetrachoric correlation in $S$ from CFPB (2024b), and the second distribution has correlation 0.67, also calculated from CFPB (2024b) and corresponding to the estimated correlation in $F$ in Table 4. For each of the distributions, we then use thresholding to determine whether each draw is affected by the late fees friction, overdraft fees friction, or both. We consider the cases where a draw is affected by at least one of the frictions as our new measure of $S$ and $F$ respectively, and calculate the average loss across these cases to determine our new measure of $L$.

[28] In this equation, $S_j$ and $L_j$ denote the empirical share at risk and age-specific dollar loss after they have been mapped from observable income bins to the model's permanent states using the procedure in Section K.3.

dollar losses from these health frictions through the same $\mathscr{L}_{it}(\mathbf{f}_i)$ channel as the direct dollar loss frictions above. We do not incorporate the colorectal cancer screening friction into the model because its estimated losses are relatively small. Unlike the other frictions, these mortality frictions require adjusting the baseline mortality schedule before re-applying each friction in the model. The observed death probabilities from the NHIS already embed the elevated mortality associated with each of these behaviors, so using them directly as the baseline and then further scaling up mortality for affected individuals would double-count the mortality contribution. We therefore deflate the observed death probabilities to construct a counterfactual baseline that removes the contribution of each of the two frictions, and then re-apply the mortality penalties to individuals who have each respective friction.[29] For statins, the mortality multiplier is computed from the cardiovascular mortality effect multiplied by the 56.9 percent share of all deaths due to cardiovascular disease reported in Section 2.6.1, so the multiplier is fixed across ages and common across income groups. The statin friction is assigned to a share $S_j F_j$ applied permanently. For smoking, the multiplier varies with both age (one value for ages 50–74 and another for ages 75+) and income group, taken from the NHIS estimates reported in Table J4. Smoking also receives an additional adjustment to capture optimal smokers: we assign the friction to a share $S_j \cdot F_j + o_j$ of the population in the model, where $o_j$ is the share of optimal smokers who do not intend to quit. Both suboptimal and optimal smokers receive the friction and face elevated mortality in the baseline simulation. However, when constructing counterfactuals that remove the smoking friction, only the suboptimal smokers ($S_j \cdot F_j$) have their friction removed; the optimal smokers retain their elevated mortality since although their mortality is the same as those smoking suboptimally under the friction, we assume they are optimizing by smoking. This is conservative: it ensures that our estimated impact of smoking reflects only the mortality cost attributable to the self-control problem.

**Definition of Current-Period Consumable Income.** To measure the impact of frictions, we report the model analogue of current-period consumable income $R_{it}$ from (1). Let $\widetilde{W}_{it}$ denote wealth entering period $t$ before that period's asset return is realized. We define:

$$R_{it}(\mathbf{f}_i) = c_{it}(\mathbf{f}_i) + \widetilde{W}_{i,t+1}(\mathbf{f}_i) - \widetilde{W}_{it}(\mathbf{f}_i) \tag{11}$$

where $\widetilde{W}_{i,t+1}$ is the wealth carried into the next period before next-period asset returns are realized. Equivalently, $\widetilde{W}_{i,t+1}$ equals liquid savings after direct friction losses, $S^L_{it} - \mathscr{L}_{it}(\mathbf{f}_i)$, plus the illiquid account balance after current-period contributions, withdrawals, employer matching, early-withdrawal penalties, and vesting, but before applying the portfolio return. This definition matches the timing convention in (1): current-period capital income is included in $R_{it}(\mathbf{f}_i)$ rather than in the change in wealth. In contrast to the empirical component construction in (3), the model lets us compute this object directly from simulated consumption and pre-return wealth.

**Limitations of Modeling Approach.** There are two important limitations to how we model these frictions. First, we model all frictions in reduced-form, remaining agnostic about possible microfoundations. This approach al-

[29] The deflation procedure is described in Section K.4.

lows us to build a tractable model that contains all of the frictions jointly, but at the same time it limits our ability to draw welfare conclusions. The second limitation is that we evaluate the impact of frictions in partial equilibrium. We do this because building a general equilibrium model of all of these frictions is obviously intractable. Nevertheless, we view our results as providing a natural starting point, given that in many cases those that are subject to the friction hold a small share of aggregate wealth.

### 4.3 Plan to Incorporate Remaining Frictions

This section discusses how we plan to incorporate the remaining frictions from Table 1 into the model.

**Not Meeting the Employer 401(k) Match.** We will model this friction by preventing affected individuals with 401(k) access from contributing to the illiquid account, so they behave as if they lack 401(k) access entirely. In the counterfactual that removes the friction, these individuals will switch to optimally choosing contributions, benefiting from the employer match and the tax advantages of the account.

**Investing in Individual Stocks.** We will model this friction by subjecting affected individuals to higher equity return volatility in their liquid account, reflecting the excess idiosyncratic risk from holding a concentrated portfolio of individual stocks. The friction will not affect the 401(k) account, given that under-diversification is uncommon in defined contribution plans.

**Investing in High-Fee Mutual Funds.** Individuals with this friction will face a reduction in the return on their equity portfolio equal to the average excess mutual fund fee, rescaled by the share of equity held in mutual funds.

**Not Refinancing a Mortgage.** Once the model incorporates endogenous homeownership, we will model this friction as a direct dollar loss subtracted from the liquid account each period for homeowners, equal to the expected savings from refinancing that are foregone due to inattention.

**Suboptimally Repaying Credit Card Debt.** We will implement this friction as a higher borrowing interest rate on the liquid asset. Because the model generates both the share of individuals who borrow and the extent of their debt, we interpret liquid-account debt as credit card debt and increase the borrowing rate for individuals with the friction, consistent with the estimated cost of suboptimal repayment allocation across multiple cards (Gathergood et al., 2019). To generate meaningful borrowing, we plan to incorporate naive present bias (Laibson et al., 2024).

### 4.4 Calibration

This section describes how we simulate from and calibrate the model. The unit of observation is the individual, so all parameters governing the income process are calibrated to individual rather than household income. The numeraire equals median individual income, which is calibrated from the PSID 2012-2019 waves at $40,499. The

general approach of our calibration strategy is to use moments, whenever possible, specific to the 2010s. This calibration is still ongoing and will be refined in future versions.

**Simulation Procedure.** The model is solved and simulated separately for each of the $2^N$ possible friction combinations with identical realizations of stochastic shocks.[30] Because the number of combinations grows exponentially in the number of frictions, this is computationally intensive. To construct the baseline simulation, we need to map the empirical friction estimates from Table 3 — which are estimated conditional on observable income measures that vary across frictions — to the model's permanent states. For each friction, we first identify the relevant population: whether an individual is in the category subject to the friction is deterministic given their state variables (e.g., individuals without a college degree for the college attendance friction, or all individuals for the direct dollar loss frictions, for which we set the model's share at risk to one as described in Section 4.2). We then map the friction probability $F_j$ — and, for the direct dollar loss frictions, the per-period loss $\lambda_j$ — from the observable income measure onto permanent income groups (sometimes interacted with education) using a procedure described in Section K.3 that infers this mapping from our model's income and mortality processes. The education frictions are first adjusted to preserve $S_j F_j$ after substituting the PSID at-risk share, then mapped from parental-income groups to child permanent-income groups using the intergenerational transition described in Section E.1. We then use the projected prevalences to assign each simulated individual a permanent friction combination, imposing the correlation structure described in Section 2.7. Specifically, for each individual, we draw a vector of latent Gaussian variables from a multivariate normal distribution with unit variances and off-diagonal entries equal to the assumed tetrachoric correlations, and we assign friction $j$ if the $j$th latent variable falls below $\Phi^{-1}(F_j)$, where $\Phi$ is the standard normal CDF and $F_j$ is the individual's projected prevalence for friction $j$. This construction preserves the marginal prevalence $F_j$ for each friction while inducing the assumed pairwise correlations across friction indicators. In the current draft, we assume that all off-diagonal correlations are zero. The health frictions are the one exception that cannot be mapped using this procedure: because the external simulation requires a mortality process as an input, and the mortality process itself depends on the health frictions, friction prevalence must be known before the external simulation can be run. Therefore, we assign the health frictions directly using the estimates of $F_j$ by permanent income group from Table 3.

**Demographics.** Each model period corresponds to one year. Individuals enter the model at age 22, retire at age 64, and die with certainty at age 96, corresponding to $a_R = 43$ and $a_T = 74$. Survival probabilities $\mathscr{D}$ are calibrated from the NHIS and vary by permanent income group. The equivalence scale parameters are $\alpha_k = 0.7$ and $\alpha_n = 0.75$, following Lusardi et al. (2017). The number of children is a cubic polynomial in age whose coefficients are estimated from the PSID, with children set to zero beyond education-specific cutoff ages.

[30] More precisely, the underlying uniform random numbers used to determine binary outcomes such as unemployment and mortality are held fixed across all $2^N$ simulations. However, because some frictions alter the thresholds for these outcomes — for example, the for-profit friction raises unemployment probabilities and the smoking friction increases mortality hazards — the realized binary outcomes can differ across friction combinations even though the underlying draws are identical.

**Education and Permanent Income Groups.** There are $N_e = 4$ education groups — no college, some college non-for-profit, some college for-profit, and 4-year college degree — and $N_\delta = 3$ permanent income groups, yielding 12 combined groups. Population shares across these groups are calibrated from the PSID. Within the some-college population — the middle two groups — the for-profit share is estimated via simulated method of distance targeting observed population shares. To estimate permanent income groups, we estimate fixed effects in individual income from the PSID following the approach in Rafkin et al. (2023). Using these estimated fixed effects, we then create groups corresponding to 0-25%, 25-75%, and 75-100%, using the mean estimated fixed effect as the fixed effect for that particular group.

**Income Process.** The intercepts $\overline{y}$ are calibrated jointly with the for-profit shares via simulated method of distance targeting median incomes by income and education groups. The deterministic age profile $f$ is a cubic polynomial in age estimated from pre-tax labor income in the PSID.[31] The stochastic parameters of the income process — persistence $\rho_z$, drift terms $B$, initial dispersion $Q_0$, age- and state-dependent volatilities $Q$, transitory shock standard deviations $R_E$, and unemployment probability function — are taken from Braxton et al. (2025). The unemployment replacement rate is $\ell = 0.4$ and the income floor is $\underline{y} =$ \$1,000 in numeraire units.

**Liquid Account.** The risk-free rate is $R^f = 1.0082$ — the average real 10-year Treasury rate between 2012 and 2019 — and the borrowing spread is $\tau_L^0 = 0.105$ — the average credit card borrowing rate computed from the SCF 2010s waves following Lee and Maxted (2023). The borrowing limit equals 25% of the deterministic component of income during working life, as in Lee and Maxted (2023), is frozen at its last working-life value during retirement, and is zero at the terminal age. The initial distribution of liquid assets is a two-component lognormal mixture calibrated from the SCF, with separate parameters for positive and negative balances by education group.

**Illiquid Account.** The 401(k) access probability is calibrated by mapping observed access rates by income quartile from the National Compensation Survey (NCS) to model income groups, using the same procedure to estimate the prevalence of frictions by permanent income groups described above. The employer match rate is $m_x = 0.5$ up to a cap of $c_x = 6\%$ of income, which are common parameters in U.S. 401(k) plans (Choukhmane, 2025). The IRS employee contribution limit is \$19,500 for ages below 50 and \$26,000 for ages 50 and above. Total contributions, including the employer match, are capped at \$57,000 and \$63,500 respectively. The early withdrawal penalty is $\phi_x = 10\%$ for real-world ages below 60 and zero otherwise. The vesting probability, which varies by age and income, is calibrated from Carranza and Goodman (2025), along with an amount vested conditional on vesting of $\nu_{\text{cond}} = 0.2$.

**Portfolio Choice.** The equity premium is $\mu_s = 0.05$ and stock return volatility is $\sigma_{rs} = 0.2$. The per-period stock market participation cost is $\tau_p =$ \$475 for all income groups, which is calibrated to match average participation

[31] Because the stochastic components of the income process (the income floor, employment shocks, and the persistent and transitory innovations) shift mean log income relative to the deterministic profile, we include an additive correction in the age profile that is calibrated from an external simulation of the income process to ensure that mean income by age and education matches the PSID targets.

rates absent the stock market participation friction that match the frictionless estimates in Choukhmane and de Silva (2026).

**Student Debt.** Student debt is repaid over $T_d = 10$ years at a spread of $\Delta_d = 0.02$ above the risk-free rate under a fixed repayment plan. The amount of debt by education group is calibrated from the PSID.

**Transfers.** The social security formula $\mathcal{T}_{ss}$ is a piecewise linear function of approximate average lifetime earnings following Catherine (2022), with bend points at 0.2 and 1 in numeraire units and replacement rates of 90%, 32%, and 15% for the three segments.[32] The EITC is approximated as a fourth-degree polynomial in taxable income with coefficients and cutoffs that vary by five-year age group, estimated from federal EITC schedules. SNAP is similarly a fourth-degree polynomial in gross income with age-group-specific coefficients. The SSI benefit cap is $\overline{y}_{\text{ssi}} = 0.2$ and the asset test threshold is $\overline{W}_{\text{ssi}} = 0.05$, following Catherine (2022). Inheritances are a cubic polynomial in age with education-specific coefficients, calibrated from the SCF.

**Income and Capital Taxes.** The income tax function $\mathcal{T}_y$ is calibrated from TAXSIM. For taxable income up to \$75,000, taxes are determined by linear interpolation of a lookup table computed at \$5 intervals. Above \$75,000, we use a log-linear approximation following Heathcote et al. (2017). We cap this approximation at 50% of taxable income and use a consumption floor of $\underline{c} = \$3{,}957$, both following Duarte et al. (2021). Capital gains taxes use 2020 federal rates averaged across filing statuses. The capital loss cap is $\overline{\mathscr{L}}_{\text{cap}} = \$3{,}000$. The preferential rate $\tau_{\text{pref}}$ is a step function of AGI and the preferential share $\omega_{\text{pref}}$ is calibrated from IRS data.

**Preferences.** The discount factor is $\beta = 0.93$ and the coefficient of relative risk aversion is $\gamma = 7$. These parameters are calibrated to generate a median wealth at retirement that matches the SCF, while also generating an average equity share absent the stock market participation friction that matches the frictionless estimates in Choukhmane and de Silva (2026). The bequest strength is $\psi_1 = 100$ and the non-homotheticity parameter is $\psi_2 = \$369{,}000$ in numeraire units, with heir income $y_{\text{heir}} = 1$. These bequest parameters are taken from De Nardi et al. (2010).

## 4.5 Model Fit

Table 5 compares model-generated moments to their empirical counterparts. The calibration is preliminary and will be updated in future versions of this draft.

The model does a reasonably good job matching moments of the income distribution across age and permanent income groups. This is to be expected, as these moments were used to estimate the parameters of the income process. Median incomes at ages 25, 35, 45, and 55 are generally close to their PSID counterparts across all three income groups. The remaining gaps are concentrated in the middle and high income groups at older ages, but the

[32] The approximation of average lifetime earnings is a polynomial in the individual's persistent income component in their final working year, with coefficients calibrated by education and permanent income group from an external simulation of the income process.

fit is substantially closer once the model moments are computed using the same permanent income groups that underlie the PSID targets.

The fit for wealth accumulation is mixed. Median total wealth is close to the SCF at ages 44–46 and 64–66, but the model overstates the 25th percentile at ages 44–46 and understates it at ages 64–66, while the pattern for the 75th percentile reverses across these two age groups. The model also overstates median liquid wealth and mean 401(k) wealth. Mean 401(k) wealth at ages 44–46 is approximately $94,364 in the model relative to $58,069 in the data, and the discrepancy is larger at ages 64–66 ($274,171 in the model relative to $118,801 in the data). The model's 401(k) participation rates of 0.39, 0.67, and 0.97 exceed the NCS counterparts of 0.23, 0.53, and 0.75. The model matches the share of early 401(k) withdrawals reasonably well — 0.28 relative to 0.25 estimated by Argento et al. (2015) — and matches the mean forfeiture share of 0.10 from Carranza and Goodman (2025).

The model matches observed stock market participation rates well across income groups: at ages 44–46, model participation rates of 0.48, 0.72, and 0.89 for the bottom 25 percent, middle 50 percent, and top 25 percent are close to the SCF values of 0.46, 0.70, and 0.88. This is expected, as these moments were targeted when calibrating risk aversion and the stock market participation cost. However, the model generates too little heterogeneity in stock shares across income groups — the model predicts equity shares of 0.42, 0.64, and 0.65 relative to data values of 0.39, 0.46, and 0.48 — and we plan to address this by allowing for heterogeneous risk aversion in future versions.

Finally, the model matches well the frictionless stock market participation rate and equity share estimated by Choukhmane and de Silva (2026), which were also targeted in the calibration. Among individuals with 401(k) access, the frictionless participation rate of 0.94 in the model is close to the estimate of 0.92, and the frictionless mean equity share of 0.81 is close to the estimate of 0.79. These moments are computed in the model after turning off only the stock market participation friction, holding all other frictions at their baseline prevalence.

# 5 Counterfactuals: Effects of Removing Each Friction

This section presents the results from counterfactuals in which we remove frictions to study their effects. To measure the impact of removing a single friction $f_i^j$, we conduct counterfactuals as follows. For each individual with friction $f_i^j = 1$ in the baseline simulation, we replace their simulation results with those from the otherwise identical simulation in which $f_i^j = 0$, leaving all other frictions unchanged. Individuals who have $f_i^j = 0$ in the baseline are unaffected — their counterfactual outcomes are identical to their baseline outcomes.[33] We also conduct a counterfactual in which we simultaneously remove all frictions for each individual, setting every $f_i^j$ to zero. Section K.5 reports results from an alternative counterfactual in which we equalize each income group's removable friction probability $F_j$ to the high-income value in Table K4 and Table K5.

[33] We also ensure that the same stochastic shocks are used, so the only source of variation between the baseline and counterfactual paths is the presence or absence of the friction itself.

## 5.1 Impact by Income Group

Table 6 reports the percent change in undiscounted lifetime consumable income, undiscounted lifetime consumption, and two measures of wealth at age 65 from removing each friction, separately by permanent income group. The first wealth column reports the percent change in total age-65 wealth within the original permanent income group, assigning zero wealth to individuals who are not alive at age 65 in a given scenario. The second reports the percent change in average age-65 wealth among those alive at age 65 in each scenario. These two percent changes are identical for frictions that do not affect survival to age 65, and differ for health frictions because these counterfactuals change the set of people alive at age 65. Consumable income is defined in (11); the corresponding level differences are reported in Table K1 in the appendix.

The largest lifetime impacts on consumption come from removing the smoking and stock market participation frictions. Removing the stock market participation friction raises lifetime consumption by approximately 2.479% for the low income group and 1.745% for the middle income group, with no effect for the high income group because its calibrated removable friction probability is zero. The effects on age-65 wealth are even more pronounced: total age-65 wealth increases by approximately 18.882% for the low income group, 5.305% for the middle income group, and 0.000% for the high income group. Because the stock market participation friction does not affect mortality, these are also the percent changes in wealth per age-65 survivor. The fact that the percent effects on wealth are largest for the low income group reflects the fact that these individuals have the lowest baseline wealth, so even moderate dollar gains translate to large percent changes. In dollar terms (Table K1), the middle income group has the largest gain: removing stock market participation raises total wealth per original group member at age 65 by approximately $5,962 for the low income group, $16,326 for the middle income group, and $0 for the high income group.

Removing the smoking friction generates large gains in lifetime consumption — approximately 3.225% for the low income group, 1.458% for the middle income group, and 0.467% for the high income group — and substantial increases in total age-65 wealth, particularly for the low income group (approximately 5.327%). These effects operate through both the mortality channel and the direct dollar-loss channel: individuals who would have died earlier due to smoking now survive into retirement, while smoking-related dollar losses also fall. Removing the smoking friction raises the probability of being alive at age 65 by approximately 3.150 pp for the low income group, 1.334 pp for the middle income group, and 0.299 pp for the high income group, as reported in Table K1. Because this counterfactual changes the survivor pool, the corresponding effects on wealth per survivor are smaller: approximately 1.038%, 0.821%, and 0.290% for the low, middle, and high income groups. These additional years of life lead to increased wealth accumulation, given that individuals now need to finance more periods post-retirement from their savings. In dollar terms, the consumption gains from removing the smoking friction are large for all three income groups (approximately $29,047, $37,676, and $23,727 for low, middle, and high income groups, respectively).

The education frictions — college attendance and 2-year for-profit attendance — generate moderate lifetime impacts, with the college attendance friction producing the larger effects. Removing the college attendance fric-

tion raises lifetime consumable income by approximately 0.927% for the low income group, 0.699% for the middle income group, and 0.183% for the high income group. The corresponding consumption effects are similar in magnitude. Removing the for-profit attendance friction raises lifetime consumption by 0.433%, 0.182%, and 0.025%, respectively. Both education counterfactuals raise age-65 wealth, consistent with higher lifetime earnings enabling greater wealth accumulation.

Among the remaining savings frictions, high-fee mutual funds have the largest effects. Removing this friction raises lifetime consumption by 0.411%, 0.773%, and 1.315% for the low, middle, and high income groups, respectively, and raises total age-65 wealth by 3.293%, 2.469%, and 3.161%. In contrast, the effects of removing low-interest account saving and individual-stock concentration are close to zero and mixed in sign. This reflects both the modest return changes induced by these frictions and endogenous portfolio and saving responses.

The direct-loss and benefit-claiming frictions generate smaller but non-negligible effects. Removing the combined late-fee and overdraft-fee friction raises lifetime consumable income by approximately 0.773% for the low income group and 0.421% for the middle income group, while removing the dominated insurance friction raises lifetime consumable income by approximately 0.004% for the low income group and 0.208% for the middle income group. Removing the EITC claiming friction raises lifetime consumption by 0.505% for the low income group, while removing the SNAP claiming friction raises it by 1.367%. A notable feature of these frictions is that their wealth effects are small and sometimes negative, reflecting the fact that agents consume part of the additional consumable income rather than save it.

The remaining health friction — failure to take statins — generates smaller lifetime effects relative to smoking, but with a similar qualitative pattern. It operates through mortality and direct dollar-loss channels and disproportionately benefits the low income group in percentage terms. Removing the statins friction raises lifetime consumption by approximately 0.470% for the low income group, 0.242% for the middle income group, and 0.147% for the high income group, with a corresponding rise in the probability of being alive at age 65 of approximately 0.671 pp for the low income group. As with smoking, the total-wealth and survivor-mean wealth columns differ because the counterfactual changes who survives to age 65. The smaller magnitude of this friction, relative to smoking, reflects its lower implied mortality penalty and smaller direct dollar losses.

The final panel of Table 6 reports the impact of simultaneously removing all frictions. The combined effects are large: lifetime consumption increases by approximately 10.908% for the low income group, 6.219% for the middle income group, and 2.278% for the high income group. The effects on total age-65 wealth are more pronounced, with increases of approximately 33.852% for the low income group, 11.708% for the middle income group, and 3.753% for the high income group. The corresponding effects on wealth per age-65 survivor are 27.397%, 9.795%, and 3.311%, respectively. The probability of being alive at age 65 also rises by approximately 3.760 pp for the low income group, 1.535 pp for the middle income group, and 0.403 pp for the high income group, which is driven by the two mortality frictions (smoking and statins).

In Figure 5, we plot the changes from Table 6 for the high permanent income group against the low permanent income group. Each of the three panels corresponds to a different outcome: lifetime consumable income (Panel

A), lifetime consumption (Panel B), and total wealth (Panel C). Across all three panels, most of the frictions lie below the 45-degree line, indicating that removing the friction has a larger effect on the low income group. The principal exception is the high-fee mutual fund friction, whose consumable-income and consumption effects are largest for the high income group.

## 5.2 Impact on Total Inequality

Table 7 reports the impact of each friction on population-wide measures of inequality in undiscounted lifetime consumable income, undiscounted lifetime consumption, and wealth at age 65. Panel A reports level differences and Panel B reports percent differences. For lifetime consumable income and consumption, we report changes in the Gini coefficient, computed over all individuals in the simulation.[34] For wealth at age 65, we report changes in the 25th and 75th percentiles and in the normalized interquartile spread (P75−P25)/P50. The first wealth block computes these statistics over the individuals who survive to age 65 in each simulation, while the second holds the sample fixed to individuals who survive to age 65 in the counterfactual without the friction. A negative change in any of these statistics indicates that removing the friction reduces inequality in that outcome.

Looking across all the frictions, a common pattern emerges: removing a friction generally reduces inequality in lifetime consumable income and consumption, and often compresses the wealth distribution relative to the median. The effects on lifetime consumable-income and consumption inequality are most pronounced for smoking. The stock market participation friction has the largest compressing effect on the survivor-conditioned wealth distribution, while smoking has a similarly important effect when the survivor sample is held fixed.

Removing the stock market participation friction has the largest effect on survivor-conditioned wealth inequality. The 25th percentile of wealth at age 65 changes by approximately $4,693 (14.217%) while the 75th percentile changes by approximately $18,969 (3.189%), indicating that the gains are large in dollar terms at both ends of the distribution but proportionally larger at the bottom. The normalized interquartile spread (P75−P25)/P50 changes by -0.1149 (-3.928%), indicating that removing this friction compresses the wealth distribution relative to the median. The Gini of lifetime consumable income changes by -0.0022 (-0.529%), while the Gini of lifetime consumption changes by -0.0017 (-0.422%).

The education frictions also reduce inequality, although the college attendance friction has the larger effect in the updated results. Removing the for-profit attendance friction changes the Gini of consumable income by -0.0006 (-0.146%) and the Gini of consumption by -0.0006 (-0.146%). The normalized interquartile wealth spread changes by -0.0046 (-0.159%). Removing the college attendance friction changes the normalized interquartile wealth spread by -0.0216 (-0.740%).

Removing the smoking friction generates the largest reductions in consumable-income and consumption inequality of any single friction: it changes the Gini of consumable income by -0.0035 (-0.844%) and the Gini of consumption by -0.0035 (-0.870%). The survivor-conditioned effect on wealth inequality is small and positive (the

[34] Results are similar if we instead measure lifetime consumable-income and consumption inequality using the standard deviation of log outcomes.

normalized interquartile wealth spread changes by 0.0273), reflecting the compositional effect of changed mortality: in the counterfactual without smoking, additional lower-wealth individuals survive to age 65, which widens the wealth distribution among survivors. In contrast, when we hold the survivor sample fixed to those alive in the counterfactual, the normalized interquartile wealth spread changes by -0.0818, indicating that removing the smoking friction compresses the wealth distribution once this survival-composition effect is removed. The remaining mortality friction, statins, generates smaller reductions in consumable-income and consumption inequality measures, consistent with its smaller lifetime impacts described above.

The savings frictions need not reduce inequality. In particular, removing the high-fee mutual fund friction changes the Gini of lifetime consumable income by 0.0027 and the Gini of lifetime consumption by 0.0024, increasing both because the counterfactual gains are largest for high-income households. The corresponding inequality effects of low-interest account saving and individual-stock concentration are close to zero.

The direct-loss and benefit-claiming frictions generate smaller but still visible effects. Removing the combined late-fee and overdraft-fee friction changes the Gini of consumable income by -0.0012 (-0.295%) and the Gini of consumption by -0.0012 (-0.301%). Removing the EITC and SNAP claiming frictions also reduces consumable-income and consumption inequality, but their wealth effects are mixed: in particular, removing the SNAP friction lowers the survivor-conditioned 25th percentile of wealth. Removing the dominated insurance friction generates smaller reductions in consumable-income and consumption inequality, with Gini changes of -0.0003 and -0.0003. These mixed wealth effects are consistent with the relatively modest per-period dollar losses and endogenous consumption responses.

The final row of Table 7 reports the combined effect of simultaneously removing all frictions. The Gini of lifetime consumable income and consumption change by -2.116% and -2.079%, respectively. The normalized interquartile wealth spread changes by -0.1025 (-3.502%) when each simulation uses its own age-65 survivor pool, and by -0.2368 (-7.737%) when the survivor pool is fixed to counterfactual survivors, indicating that the wealth distribution compresses relative to the median when all frictions are removed.

# 6 Conclusion

This paper provides a first systematic quantification of the contribution of decision-making frictions to inequality in income, consumption, and wealth. We estimate the prevalence and financial impact of 19 frictions spanning education, savings, borrowing, insurance, benefits, and health, and find that these frictions disproportionately affect lower-income individuals: the aggregate annual loss is approximately 8.23% of annual income for the bottom quartile relative to 2.96% for the top quartile. The total loss for low-income households is approximately 8.5 times larger than the effect of a major EITC expansion. We incorporate a subset of these frictions into a life cycle model and find that removing them tends to reduce inequality in lifetime consumable income and consumption, with smoking playing a particularly large role among the frictions currently incorporated.

Our analysis is a work in progress along several dimensions. On the empirical side, in addition to refining

our existing estimates, we are in the process of expanding the set of frictions to include other behaviors such as a lack of mortgage shopping, a tendency to over-insure small risks (e.g., warranties), and excess savings held in low-interest transactional accounts. In the life cycle model, we plan to incorporate the remaining frictions from Table 1 that have not yet been included, add endogenous homeownership and medical expenses in retirement, allow for income-group-specific discount factors and present bias, and introduce heterogeneous risk aversion. We also plan to examine the robustness of our model results by varying key assumptions, including the correlation in the prevalence of different frictions across individuals, the persistence of frictions within a given individual, individuals' sophistication about the likelihood of being subject to future frictions, and the extent to which individuals unaffected by a friction benefit indirectly from those who are (Gabaix and Laibson, 2006). The preliminary calibration will also be updated as we refine the model and incorporate additional frictions.

Table 2: Decision-Making Frictions, Data Sources Summarized

| No. | Category | Friction | $S_j$ Data Source | $F_j$ Data Source | $L_j$ Data Source | Income Distribution to Determine $j$ |
|---|---|---|---|---|---|---|
| 1 | Education | Not Attending College Due to Frictions | Snyder et al. (2019) + BPS (2017) | Prior Literature | Mountjoy (2025) + Model | Parental |
| 2 | Education | Attending 2-Year For-Profit Colleges | Snyder et al. (2019) + BPS (2017) | Snyder et al. (2019) + BPS (2017) | Cellini and Turner (2019) + Model + NCES (2023) | Parental |
| 3 | Savings | Not Meeting the Employer 401(k) Match | Bureau of Labor Statistics (2020a) | Carranza et al. (2026) | Bureau of Labor Statistics (2020a) + Carranza et al. (2026) | Current |
| 4 | Savings | Not Investing in Stock Mutual Funds | SCF 2013-2019 | SCF 2013-2019 | SCF 2013-2019 | Current |
| 5 | Savings | Saving in Low Interest Accounts | SCF 2013-2019 | SCF 2013-2019 | SCF 2013-2019 + The U.S. Federal Reserve (2026) | Current |
| 6 | Savings | Investing in Individual Stocks | SCF 2013-2019 | SCF 2013-2019 | SCF 2013-2019 | Current |
| 7 | Savings | Investing in High-Fee Mutual Funds | SCF 2013-2019 | Choi et al. (2010) | CRSP 2011-2019 + SCF 2013-2019 | Current |
| 8 | Borrowing | Not Refinancing a Mortgage | SCF 2013-2019 | Andersen et al. (2020) | House Purchases Simulation | Current |
| 9 | Borrowing | Not Getting an Additional Mortgage Quote | SCF 2013-2019 | Bhutta et al. (2026) | Bhutta et al. (2026) + House Purchases Simulation | Current |
| 10 | Borrowing | Suboptimally Repaying Credit Card Debt | SCF 2013-2019 | Gathergood et al. (2019) | Gathergood et al. (2019) + SCF 2013-2019 | Current |
| 11 | Borrowing | Paying Late Fees | CFPB Making Ends Meet Survey 2023-2025 | CFPB Making Ends Meet Survey 2023-2025 | CFPB Making Ends Meet Survey 2023-2025 + Low et al. (2017) | Current |
| 12 | Borrowing | Paying Overdraft Fees | CFPB Making Ends Meet Survey 2023-2025 + CFPB (2021) | CFPB Making Ends Meet Survey 2023-2025 | CFPB Making Ends Meet Survey 2023-2025 | Current |
| 13 | Insurance | Choosing Dominated Health Insurance | SCF 2013-2019 + Liu and Sydnor (2022) | Bhargava et al. (2017) | Liu and Sydnor (2022) | Current |
| 14 | Insurance | Suboptimally Lapsing Life Insurance | SCF 2013-2019 | Gottlieb and Smetters (2021) + SCF 2013-2019 | Compulife 2019 + SCF 2013-2019 | Current |
| 15 | Benefits | Not Claiming EITC Benefits | PSID 2011-2019 | Coleman et al. (2024) | PSID Simulation | Current |
| 16 | Benefits | Not Claiming SNAP Benefits | PSID 2011-2019 | Vigil (2022) + PSID 2011-2019 | PSID Simulation | Current |
| 17 | Health | Not Taking Statin Medications | NHIS 2010-2018 | Verma et al. (2017) | Prior Literature + Model | Current |
| 18 | Health | Not Screening for Colon Cancer | Recommended Screening Guidelines + NHIS 2010-2018 | NHIS 2010-2018 | Shroff et al. (2014) + Model | Current |
| 19 | Health | Failing to Quit Smoking | NHIS 2010-2018 | NHIS 2010-2018 | NHIS 2010-2018 + Model | Current |

Table 3: Empirical Evidence of all Frictions

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | |
| Low Income | 0.405 | 0.323 | \$811 | \$106 |
| | (0.013) | (0.052) | [369, 1,219] | [47, 173] |
| Middle Income | 0.351 | 0.275 | \$3,201 | \$310 |
| | (0.010) | (0.051) | [1,812, 4,472] | [151, 470] |
| High Income | 0.296 | 0.224 | \$5,798 | \$385 |
| | (0.009) | (0.042) | [3,453, 7,951] | [193, 569] |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | |
| Low Income | 0.265 | 0.151 | \$1,050 | \$42 |
| | (–) | (–) | [–] | [–] |
| Middle Income | 0.252 | 0.110 | \$2,719 | \$75 |
| | (–) | (–) | [–] | [–] |
| High Income | 0.220 | 0.078 | \$5,217 | \$90 |
| | (–) | (–) | [–] | [–] |
| *Panel C: Not Meeting the Employer 401(k) Match* | | | | |
| Low Income | 0.292 | 0.572 | \$395 | \$66 |
| | (0.011) | (0.005) | [386, 416] | [61, 72] |
| Middle Income | 0.462 | 0.299 | \$1,438 | \$199 |
| | (0.005) | (0.002) | [1,387, 1,472] | [190, 206] |
| High Income | 0.517 | 0.197 | \$2,677 | \$272 |
| | (0.005) | (0.003) | [2,528, 2,793] | [261, 292] |
| *Panel D: Not Investing in Stock Mutual Funds* | | | | |
| Low Income | 0.326 | 0.646 | \$354 | \$75 |
| | (0.008) | (0.015) | [297, 436] | [61, 92] |
| Middle Income | 0.643 | 0.305 | \$959 | \$188 |
| | (0.006) | (0.008) | [887, 1,039] | [171, 206] |
| High Income | 0.867 | 0.129 | \$2,615 | \$293 |
| | (0.006) | (0.007) | [2,193, 3,076] | [239, 354] |
| *Panel E: Saving in Low Interest Accounts* | | | | |
| Low Income | 0.281 | 0.634 | \$48 | \$8 |
| | (0.008) | (0.016) | [41, 59] | [7, 11] |
| Middle Income | 0.451 | 0.583 | \$97 | \$26 |
| | (0.006) | (0.009) | [88, 106] | [23, 28] |
| High Income | 0.686 | 0.491 | \$202 | \$68 |
| | (0.008) | (0.010) | [183, 223] | [61, 76] |

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Table 3 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Panel F: Investing in Individual Stocks* | | | | |
| Low Income | 0.281 | 0.027 | \$937 | \$7 |
| | (0.008) | (0.006) | [483, 1,813] | [3, 16] |
| Middle Income | 0.451 | 0.050 | \$1,446 | \$33 |
| | (0.006) | (0.004) | [1,044, 1,997] | [22, 46] |
| High Income | 0.686 | 0.061 | \$3,462 | \$146 |
| | (0.008) | (0.005) | [2,079, 5,285] | [86, 230] |
| *Panel G: Investing in High-Fee Mutual Funds* | | | | |
| Low Income | 0.136 | 0.910 | \$79 | \$10 |
| | (0.006) | (0.029) | [65, 112] | [8, 14] |
| Middle Income | 0.498 | 0.910 | \$168 | \$76 |
| | (0.007) | (0.029) | [161, 183] | [69, 86] |
| High Income | 0.781 | 0.910 | \$987 | \$702 |
| | (0.008) | (0.029) | [924, 1,047] | [639, 769] |
| *Panel H: Not Refinancing a Mortgage* | | | | |
| Low Income | 0.152 | 0.833 | \$350 | \$53 |
| | (0.012) | (0.007) | [234, 486] | [35, 78] |
| Middle Income | 0.381 | 0.702 | \$191 | \$73 |
| | (0.008) | (0.006) | [173, 211] | [65, 81] |
| High Income | 0.498 | 0.672 | \$294 | \$146 |
| | (0.010) | (0.006) | [266, 333] | [132, 169] |
| *Panel I: Not Getting an Additional Mortgage Quote* | | | | |
| Low Income | 0.151 | 0.606 | \$143 | \$13 |
| | (0.011) | (0.000) | [107, 205] | [9, 19] |
| Middle Income | 0.378 | 0.524 | \$137 | \$27 |
| | (0.008) | (0.000) | [126, 149] | [25, 30] |
| High Income | 0.493 | 0.472 | \$217 | \$50 |
| | (0.009) | (0.000) | [196, 239] | [46, 56] |
| *Panel J: Suboptimally Repaying Credit Card Debt* | | | | |
| Low Income | 0.144 | 0.880 | \$129 | \$16 |
| | (0.007) | (0.001) | [114, 145] | [14, 19] |
| Middle Income | 0.305 | 0.880 | \$177 | \$47 |
| | (0.006) | (0.001) | [165, 190] | [44, 52] |
| High Income | 0.285 | 0.880 | \$263 | \$66 |
| | (0.008) | (0.001) | [234, 295] | [57, 74] |

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Table 3 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Panel K: Paying Late Fees* | | | | |
| Low Income | 0.463 | 0.311 | $406 | $57 |
| | (0.013) | (0.017) | [381, 425] | [49, 64] |
| Middle Income | 0.736 | 0.251 | $406 | $73 |
| | (0.004) | (0.010) | [381, 425] | [70, 78] |
| High Income | 0.827 | 0.133 | $406 | $44 |
| | (0.007) | (0.011) | [381, 425] | [38, 50] |
| *Panel L: Paying Overdraft Fees* | | | | |
| Low Income | 0.776 | 0.435 | $325 | $110 |
| | (0.014) | (0.020) | [291, 358] | [95, 127] |
| Middle Income | 0.963 | 0.351 | $297 | $100 |
| | (0.004) | (0.014) | [270, 338] | [89, 119] |
| High Income | 0.992 | 0.176 | $255 | $44 |
| | (0.003) | (0.014) | [208, 299] | [34, 56] |
| *Panel M: Choosing Dominated Health Insurance* | | | | |
| Low Income | 0.065 | 0.620 | $1,121 | $45 |
| | (0.005) | (0.006) | [1,111, 1,132] | [38, 53] |
| Middle Income | 0.202 | 0.520 | $1,121 | $118 |
| | (0.014) | (0.005) | [1,111, 1,132] | [101, 133] |
| High Income | 0.249 | 0.400 | $1,121 | $112 |
| | (0.017) | (0.006) | [1,111, 1,132] | [96, 128] |
| *Panel N: Suboptimally Lapsing Life Insurance* | | | | |
| Low Income | 0.132 | 0.181 | $50 | $1 |
| | (0.005) | (0.006) | [46, 64] | [1, 2] |
| Middle Income | 0.286 | 0.170 | $115 | $6 |
| | (0.006) | (0.002) | [109, 120] | [5, 6] |
| High Income | 0.343 | 0.157 | $296 | $16 |
| | (0.007) | (0.002) | [286, 313] | [15, 17] |
| *Panel O: Not Claiming EITC Benefits* | | | | |
| Low Income | 0.394 | 0.223 | $978 | $86 |
| | (0.009) | – | [935, 1,017] | [81, 91] |
| Middle Income | 0.046 | 0.223 | $1,082 | $11 |
| | (0.002) | – | [1,007, 1,156] | [10, 12] |
| High Income | 0.001 | 0.223 | $1,016 | $0 |
| | (0.000) | – | [601, 1,550] | [0, 0] |

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Table 3 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Panel P: Not Claiming SNAP Benefits* | | | | |
| Low Income | 0.394<br>(0.009) | 0.580<br>– | $1,115<br>[1,059, 1,181] | $253<br>[236, 274] |
| Middle Income | 0.020<br>(0.003) | 0.580<br>– | $1,243<br>[907, 1,590] | $13<br>[8, 18] |
| High Income | 0.001<br>(0.001) | 0.580<br>– | $0<br>[0, 0] | $0<br>[0, 0] |
| *Panel Q: Not Taking Statin Medications* | | | | |
| Low Income | 0.443<br>(0.005) | 0.469<br>(0.024) | $435<br>[306, 478] | $90<br>[62, 104] |
| Middle Income | 0.449<br>(0.004) | 0.404<br>(0.023) | $633<br>[522, 782] | $115<br>[93, 145] |
| High Income | 0.478<br>(0.007) | 0.357<br>(0.019) | $751<br>[639, 924] | $128<br>[107, 166] |
| *Panel R: Not Screening for Colon Cancer* | | | | |
| Low Income | 0.465<br>(0.002) | 0.619<br>(0.005) | $40<br>[29, 41] | $12<br>[8, 12] |
| Middle Income | 0.466<br>(0.001) | 0.524<br>(0.004) | $43<br>[33, 51] | $11<br>[8, 13] |
| High Income | 0.461<br>(0.002) | 0.439<br>(0.006) | $45<br>[28, 46] | $9<br>[6, 9] |
| *Panel S: Failing to Quit Smoking* | | | | |
| Low Income | 0.202<br>(0.013) | 0.563<br>(0.031) | $5,595<br>[4,935, 5,972] | $638<br>[486, 746] |
| Middle Income | 0.188<br>(0.011) | 0.414<br>(0.028) | $8,087<br>[6,850, 8,523] | $628<br>[461, 721] |
| High Income | 0.168<br>(0.013) | 0.240<br>(0.047) | $8,816<br>[6,059, 17,551] | $355<br>[156, 669] |
| **Summary Panel** | | | | |
| *Mean* | | | | |
| Low Income | 0.323 | 0.512 | $624.32 | $95.21 |
| Middle Income | 0.410 | 0.424 | $1,067.79 | $114.05 |
| High Income | 0.469 | 0.352 | $1,553.79 | $142.32 |
| *Sum* | | | | |
| *Dollar Amount* | | | | |

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Table 3 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| Low Income | | | | \$1,805<br>[\$1,652, \$1,958] |
| Middle Income | | | | \$2,154<br>[\$1,955, \$2,353] |
| High Income | | | | \$2,693<br>[\$2,422, \$2,964] |
| *Percent of Mean Income* | | | | |
| Low Income | | | | 8.23%<br>[7.53%, 8.93%] |
| Middle Income | | | | 4.98%<br>[4.52%, 5.44%] |
| High Income | | | | 2.96%<br>[2.66%, 3.26%] |

*For the mortgage refinancing friction, $F_j$ is modeled as an i.i.d. friction across the years, as opposed to assuming that a fixed fraction of individuals have a persistent friction. So, our estimates for $L_j$ already implicitly incorporate the probability of checking for refinancing. For all other frictions, $F_j$ is the annual probability of committing the friction, assuming perfect auto-correlation in who commits the frictions across years, and $L_j$ is the average loss conditional on committing the friction.

Table 4: Correlations Across Financial and Health Frictions

| | Not Investing in Stock Mutual Funds | Saving in Low Interest Accounts | Paying Late Fees | Choosing Domi-nated Health Insurance | Failing to Quit Smoking |
|---|---|---|---|---|---|
| Investing in Individual Stocks | -0.055<br>(0.017) | -0.238<br>(0.014) | X | X | X |
| Not Investing in Stock Mutual Funds | 1.000 | 0.027<br>(0.010) | X | X | X |
| Paying Overdraft Fees | X | X | 0.670<br>(0.021) | X | X |
| Not Meeting the Employer 401(k) Match | X | X | X | 0.137<br>(0.025) | X |
| Not Screening for Colon Cancer | X | X | X | X | 0.074<br>(0.020) |
| **Precision-Weighted Average Correlation** | | | 0.032<br>(0.006) | | |

*Notes:* This table reports correlations estimated via bivariate probit models. Standard errors are reported in parentheses.

Table 5: Comparison of Model and Data Moments

| Moment Description | Model Value | Data Value | Data Source |
|---|---|---|---|
| Median Labor Income at Ages 24-26, Bottom 25% | $13,507 | $12,223 | PSID |
| Median Labor Income at Ages 24-26, Middle 50% | $34,132 | $31,647 | PSID |
| Median Labor Income at Ages 24-26, Top 25% | $64,206 | $64,939 | PSID |
| Median Labor Income at Ages 34-36, Bottom 25% | $14,270 | $14,783 | PSID |
| Median Labor Income at Ages 34-36, Middle 50% | $47,078 | $44,446 | PSID |
| Median Labor Income at Ages 34-36, Top 25% | $93,976 | $87,462 | PSID |
| Median Labor Income at Ages 44-46, Bottom 25% | $12,911 | $14,667 | PSID |
| Median Labor Income at Ages 44-46, Middle 50% | $49,528 | $44,296 | PSID |
| Median Labor Income at Ages 44-46, Top 25% | $104,063 | $92,834 | PSID |
| Median Labor Income at Ages 54-56, Bottom 25% | $9,303 | $8,975 | PSID |
| Median Labor Income at Ages 54-56, Middle 50% | $45,398 | $42,594 | PSID |
| Median Labor Income at Ages 54-56, Top 25% | $99,182 | $91,670 | PSID |
| Median Total Wealth at Ages 24-26 | $15,121 | $4,338 | SCF |
| Median Total Wealth at Ages 44-46 | $65,873 | $66,001 | SCF |
| Median Total Wealth at Ages 64-66 | $182,920 | $176,036 | SCF |
| P25 Total Wealth at Ages 44-46 | $17,683 | $9,904 | SCF |
| P25 Total Wealth at Ages 64-66 | $31,530 | $37,093 | SCF |
| P75 Total Wealth at Ages 44-46 | $201,284 | $255,948 | SCF |
| P75 Total Wealth at Ages 64-66 | $575,958 | $521,894 | SCF |
| Median Liquid Wealth at Ages 44-46 | $18,642 | $11,110 | SCF |
| Median Liquid Wealth at Ages 64-66 | $34,887 | $22,635 | SCF |
| 401(k) Participation at Age 45, Bottom 25% | 0.39 | 0.23 | NCS |
| 401(k) Participation at Age 45, Middle 50% | 0.67 | 0.53 | NCS |
| 401(k) Participation at Age 45, Top 25% | 0.97 | 0.75 | NCS |
| Mean 401(k) Wealth at Ages 44-46 | $94,364 | $58,069 | SCF |
| Mean 401(k) Wealth at Ages 64-66 | $274,171 | $118,801 | SCF |
| Share with Early 401(k) Withdrawals | 0.28 | 0.25 | ABS15 |
| Mean 401(k) Forfeiture Share | 0.10 | 0.10 | CG25 |
| Stock Market Participation at Ages 44-46, Bottom 25% | 0.48 | 0.46 | SCF |
| Stock Market Participation at Ages 44-46, Middle 50% | 0.72 | 0.70 | SCF |
| Stock Market Participation at Ages 44-46, Top 25% | 0.89 | 0.88 | SCF |
| Mean Stock Share at Ages 44-46, Bottom 25% | 0.42 | 0.39 | SCF |
| Mean Stock Share at Ages 44-46, Middle 50% | 0.64 | 0.46 | SCF |
| Mean Stock Share at Ages 44-46, Top 25% | 0.65 | 0.48 | SCF |
| Stock Market Participation at Age 45, Frictionless | 0.94 | 0.92 | CD26 |
| Mean Stock Share at Age 45, Frictionless | 0.81 | 0.79 | CD26 |
| Share Borrowing on Credit Cards at Ages 22-64 | 0.15 | 0.50 | SCF |

*Notes:* Each row compares a model-generated moment to its empirical counterpart. All model moments are computed from the baseline simulation with all frictions turned on at their estimated prevalence, except for the two CD26 moments labeled "Frictionless," which are computed in both the data and model conditional on 401(k) access. In the model, these moments are computed after turning off only the stock market participation friction. The labels "Bottom 25%," "Middle 50%," and "Top 25%" refer to the corresponding groups of the relevant income distribution. The PSID median labor-income moments use permanent income groups constructed from individual labor-income fixed effects, while the NCS 401(k) participation moments use the corresponding income quartiles. The SCF portfolio moments use prior-year total pre-tax, pre-transfer income; in the model, these groups are constructed separately within each aggregate return path and pooled across ages 44–46. Income and portfolio moments reported for three-year age windows pool all observations in the stated age range. Data sources: PSID (Panel Study of Income Dynamics), SCF (Survey of Consumer Finances), NCS (National Compensation Survey), ABS15 (Argento et al., 2015), CG25 (Carranza and Goodman, 2025), and CD26 (Choukhmane and de Silva, 2026).

Table 6: Model Results: Effects of Removing Frictions by Income Group

| Income Group ($j$) | $\Delta R_{sum}$ | $\Delta$Consumption$_{sum}$ | $\Delta\sum$Wealth$_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta$Survival$_{65}$ |
|---|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | | |
| Low | 0.927% | 0.812% | 2.135% | 2.135% | 0.000% |
| Middle | 0.699% | 0.668% | 1.154% | 1.154% | 0.000% |
| High | 0.183% | 0.179% | 0.236% | 0.236% | 0.000% |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | | |
| Low | 0.449% | 0.433% | 0.276% | 0.276% | 0.000% |
| Middle | 0.182% | 0.182% | 0.201% | 0.201% | 0.000% |
| High | 0.025% | 0.025% | 0.028% | 0.028% | 0.000% |
| *Panel C: Not Investing in Stock Mutual Funds* | | | | | |
| Low | 2.991% | 2.479% | 18.882% | 18.882% | 0.000% |
| Middle | 2.069% | 1.745% | 5.305% | 5.305% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel D: Saving in Low Interest Accounts* | | | | | |
| Low | 0.120% | 0.113% | 0.269% | 0.269% | 0.000% |
| Middle | 0.038% | 0.050% | -0.199% | -0.199% | 0.000% |
| High | -0.029% | -0.014% | -0.177% | -0.177% | 0.000% |
| *Panel E: Investing in Individual Stocks* | | | | | |
| Low | -0.006% | -0.005% | -0.013% | -0.013% | 0.000% |
| Middle | -0.004% | 0.007% | -0.191% | -0.191% | 0.000% |
| High | 0.036% | 0.033% | -0.041% | -0.041% | 0.000% |
| *Panel F: Investing in High-Fee Mutual Funds* | | | | | |
| Low | 0.501% | 0.411% | 3.293% | 3.293% | 0.000% |
| Middle | 0.928% | 0.773% | 2.469% | 2.469% | 0.000% |
| High | 1.559% | 1.315% | 3.161% | 3.161% | 0.000% |
| *Panel G: Paying Late Fees and Paying Overdraft Fees* | | | | | |
| Low | 0.773% | 0.743% | -0.567% | -0.567% | 0.000% |
| Middle | 0.421% | 0.453% | -0.391% | -0.391% | 0.000% |
| High | 0.046% | 0.050% | -0.040% | -0.040% | 0.000% |

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Table 6 – continued from previous page

| Income Group ($j$) | $\Delta R_{sum}$ | $\Delta\text{Consumption}_{sum}$ | $\Delta\sum\text{Wealth}_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta\text{Survival}_{65}$ |
|---|---|---|---|---|---|
| *Panel H: Choosing Dominated Health Insurance* | | | | | |
| Low | 0.004% | 0.003% | 0.050% | 0.050% | 0.000% |
| Middle | 0.208% | 0.207% | 0.155% | 0.155% | 0.000% |
| High | 0.085% | 0.086% | 0.051% | 0.051% | 0.000% |
| *Panel I: Not Claiming EITC Benefits* | | | | | |
| Low | 0.522% | 0.505% | 0.152% | 0.152% | 0.000% |
| Middle | 0.024% | 0.030% | -0.087% | -0.087% | 0.000% |
| High | -0.008% | -0.006% | -0.051% | -0.051% | 0.000% |
| *Panel J: Not Claiming SNAP Benefits* | | | | | |
| Low | 1.436% | 1.367% | -0.700% | -0.700% | 0.000% |
| Middle | 0.077% | 0.100% | -0.489% | -0.489% | 0.000% |
| High | -0.024% | -0.014% | -0.215% | -0.215% | 0.000% |
| *Panel K: Not Taking Statin Medications* | | | | | |
| Low | 0.445% | 0.470% | 1.496% | 0.586% | 0.905% |
| Middle | 0.207% | 0.242% | 0.491% | 0.229% | 0.262% |
| High | 0.111% | 0.147% | 0.223% | 0.113% | 0.110% |
| *Panel L: Failing to Quit Smoking* | | | | | |
| Low | 3.126% | 3.225% | 5.327% | 1.038% | 4.245% |
| Middle | 1.203% | 1.458% | 2.347% | 0.821% | 1.514% |
| High | 0.367% | 0.467% | 0.609% | 0.290% | 0.318% |
| *Panel M: All Frictions* | | | | | |
| Low | 11.601% | 10.908% | 33.852% | 27.397% | 5.067% |
| Middle | 6.393% | 6.219% | 11.708% | 9.795% | 1.742% |
| High | 2.352% | 2.278% | 3.753% | 3.311% | 0.428% |

*Notes:* Panels A–L report the average lifetime impact of removing a single friction, expressed as a percent change. Panel M reports the impact of simultaneously removing all frictions. All variables with subscript $sum$ denote undiscounted lifetime sums. $\Delta R_{sum}$ is the percent change in the undiscounted lifetime sum of current-period consumable income, as defined in (11). $\Delta\text{Consumption}_{sum}$ is the percent change in the undiscounted lifetime sum of consumption. Let $W_{i65}$ denote total wealth (liquid plus 401(k) assets) for individual $i$ at age 65. $\Delta\sum\text{Wealth}_{65}$ is the percent change in $\sum_i W_{i65}$ within the permanent income group, assigning zero wealth in a scenario if an individual is not alive at age 65. $\Delta\overline{\text{Wealth}}_{65}$ is the percent change in average $W_{i65}$ among individuals alive at age 65 in each scenario. $\Delta\text{Survival}_{65}$ is the percent change in the probability of being alive at age 65 within the income group. The two wealth columns are identical for frictions that do not affect survival to age 65 and can differ for health frictions because the set of survivors changes. See Table K1 for the corresponding level differences.

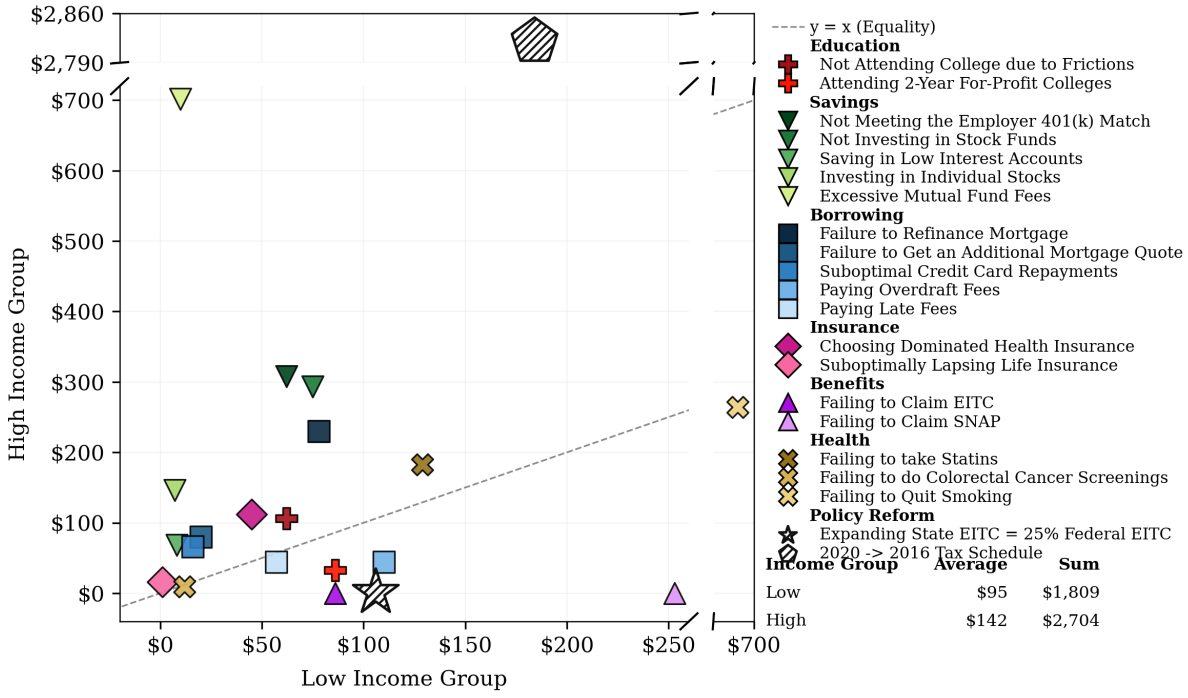
Table 7: Model Results: Effects of Removing Frictions on Total Inequality

| Friction | $R_{sum}$ | $\text{Consumption}_{sum}$ | $\text{Wealth}_{65}$ | | | $\text{Wealth}_{65}$ \| Counterfactual $\text{Survival}_{65} = 1$ | | |
|---|---|---|---|---|---|---|---|---|
| Inequality Metric | Gini | Gini | P25 | P75 | $\frac{\text{P75}-\text{P25}}{\text{P50}}$ | P25 | P75 | $\frac{\text{P75}-\text{P25}}{\text{P50}}$ |
| Value in Baseline | 0.4123 | 0.4033 | $33,012 | $594,869 | 2.9261 | · | · | · |
| *Panel A: Level Change in Inequality Metric* | | | | | | | | |
| Not Attending College Due to Frictions | -0.0012 | -0.0011 | $876 | $4,704 | -0.0216 | $876 | $4,704 | -0.0216 |
| Attending 2-Year For-Profit Colleges | -0.0006 | -0.0006 | $199 | $982 | -0.0046 | $199 | $982 | -0.0046 |
| Not Investing in Stock Mutual Funds | -0.0022 | -0.0017 | $4,693 | $18,969 | -0.1149 | $4,693 | $18,969 | -0.1149 |
| Saving in Low Interest Accounts | -0.0001 | -0.0000 | $318 | -$1,103 | -0.0055 | $318 | -$1,103 | -0.0055 |
| Investing in Individual Stocks | -0.0000 | 0.0000 | $64 | $72 | -0.0035 | $64 | $72 | -0.0035 |
| Investing in High-Fee Mutual Funds | 0.0027 | 0.0024 | $1,172 | $16,160 | 0.0134 | $1,172 | $16,160 | 0.0134 |
| Paying Late Fees and Paying Overdraft Fees | -0.0012 | -0.0012 | -$434 | -$1,379 | 0.0179 | -$434 | -$1,379 | 0.0179 |
| Choosing Dominated Health Insurance | -0.0003 | -0.0003 | $147 | $505 | -0.0067 | $147 | $505 | -0.0067 |
| Not Claiming EITC Benefits | -0.0005 | -0.0005 | $32 | -$402 | 0.0012 | $32 | -$402 | 0.0012 |
| Not Claiming SNAP Benefits | -0.0015 | -0.0015 | -$754 | -$1,870 | 0.0255 | -$754 | -$1,870 | 0.0255 |
| Not Taking Statin Medications | -0.0006 | -0.0006 | -$127 | -$206 | 0.0020 | $850 | $1,940 | -0.0201 |
| Not Quitting Smoking | -0.0035 | -0.0035 | -$1,069 | -$1,660 | 0.0273 | $3,266 | $9,276 | -0.0818 |
| All Frictions | -0.0087 | -0.0084 | $5,812 | $36,238 | -0.1025 | $10,851 | $48,777 | -0.2368 |
| *Panel B: Percent Change in Inequality Metric* | | | | | | | | |
| Not Attending College Due to Frictions | -0.298% | -0.281% | 2.653% | 0.791% | -0.740% | 2.653% | 0.791% | -0.740% |
| Attending 2-Year For-Profit Colleges | -0.146% | -0.146% | 0.604% | 0.165% | -0.159% | 0.604% | 0.165% | -0.159% |
| Not Investing in Stock Mutual Funds | -0.529% | -0.422% | 14.217% | 3.189% | -3.928% | 14.217% | 3.189% | -3.928% |
| Saving in Low Interest Accounts | -0.016% | -0.002% | 0.962% | -0.185% | -0.188% | 0.962% | -0.185% | -0.188% |
| Investing in Individual Stocks | -0.003% | 0.010% | 0.194% | 0.012% | -0.119% | 0.194% | 0.012% | -0.119% |
| Investing in High-Fee Mutual Funds | 0.665% | 0.594% | 3.550% | 2.716% | 0.459% | 3.550% | 2.716% | 0.459% |
| Paying Late Fees and Paying Overdraft Fees | -0.295% | -0.301% | -1.314% | -0.232% | 0.613% | -1.314% | -0.232% | 0.613% |
| Choosing Dominated Health Insurance | -0.067% | -0.066% | 0.445% | 0.085% | -0.229% | 0.445% | 0.085% | -0.229% |
| Not Claiming EITC Benefits | -0.132% | -0.136% | 0.096% | -0.068% | 0.041% | 0.096% | -0.068% | 0.041% |
| Not Claiming SNAP Benefits | -0.358% | -0.363% | -2.284% | -0.314% | 0.870% | -2.284% | -0.314% | 0.870% |
| Not Taking Statin Medications | -0.146% | -0.139% | -0.385% | -0.035% | 0.068% | 2.653% | 0.327% | -0.682% |
| Not Quitting Smoking | -0.844% | -0.870% | -3.239% | -0.279% | 0.932% | 11.388% | 1.589% | -2.696% |
| All Frictions | -2.116% | -2.079% | 17.605% | 6.092% | -3.502% | 38.789% | 8.376% | -7.737% |

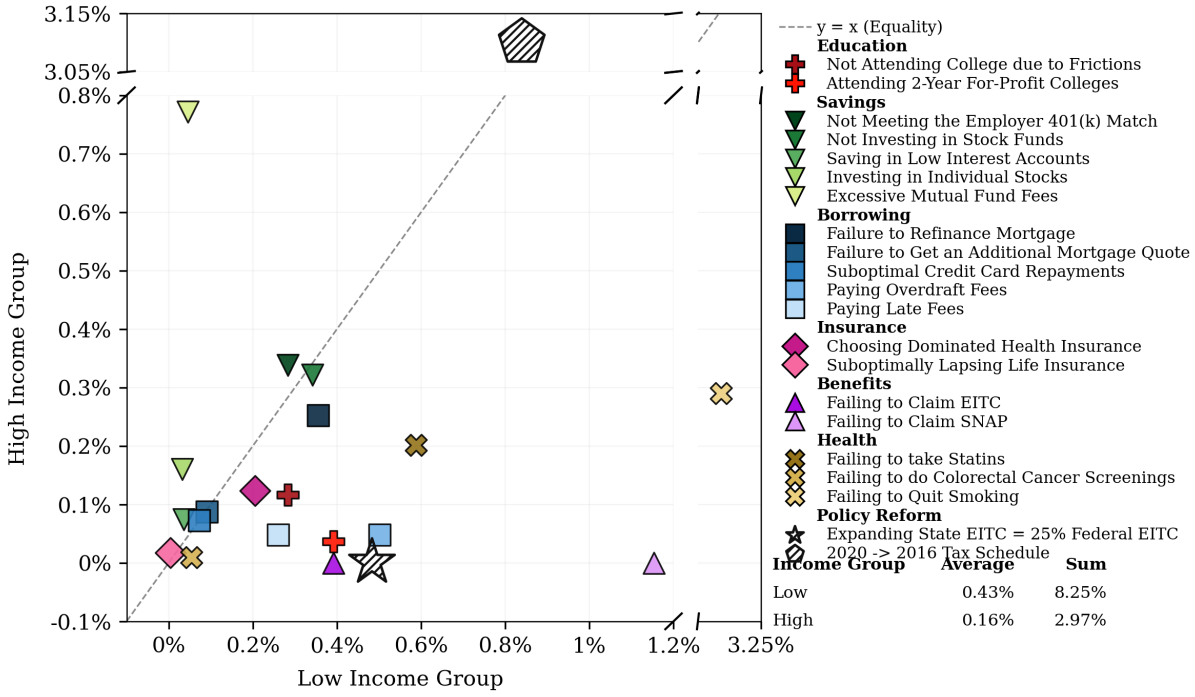
*Notes:* This table reports the impact of each friction on population-wide inequality in lifetime outcomes. All variables with subscript $sum$ denote undiscounted lifetime sums. Current-period consumable income is defined in (11). Each row corresponds to a single friction; the reported value is the change in the distributional statistic when that friction is removed, holding all other frictions at their baseline prevalence. The final row reports the impact of simultaneously removing all frictions. The first row indicates the outcome whose distribution is being measured, the "Inequality Metric" row indicates the specific distributional statistic, and the "Value in Baseline" row reports each statistic's value in the baseline simulation with all frictions on. In this baseline row, the first wealth block computes age-65 wealth statistics over individuals who survive to age 65 in the baseline simulation; the fixed-counterfactual-survivor wealth cells are shown as · because the corresponding survivor set is defined separately for each counterfactual row. Panel A reports level changes; Panel B reports percent changes relative to the baseline statistic. Gini is the Gini coefficient. The first wealth block computes age-65 wealth statistics over individuals who survive to age 65 in each respective simulation, so the baseline and counterfactual percentiles may reflect different sets of survivors. The second wealth block computes the same statistics for the fixed set of individuals who survive to age 65 in the counterfactual simulation; for individuals in this set who are not alive at age 65 in the baseline simulation because they are subject to the friction, their wealth in the baseline is set to zero. P25 and P75 are the 25th and 75th percentiles of wealth at age 65. (P75−P25)/P50 is the interquartile spread of wealth at age 65 normalized by the median.

Figure 1: Expected Annual Losses Across Frictions

*Panel A: Expected Annual Dollar Loss, SFL*



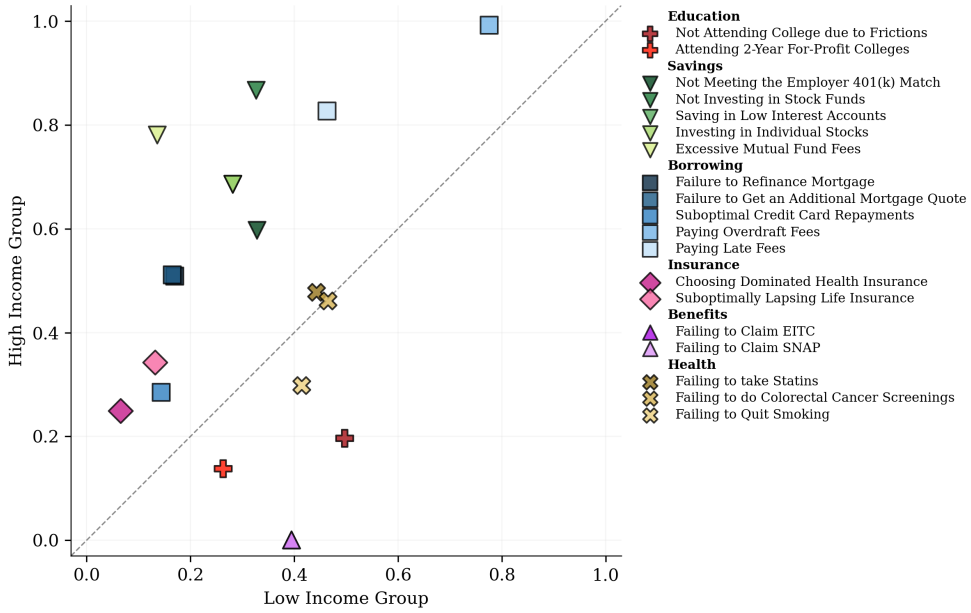

*Panel B: Expected Annual Loss as Percentage of Income, SFL/ y*




*Notes:* Panel B reports annual losses as a percentage of income, computed by dividing each income group's mean expected annual loss by their mean annual post-tax post-transfer income in our model. We divide the low-income group's losses by $14,546, the middle-income group's losses by $38,658, and the high-income group's losses by $67,875.

Figure 2: Decomposition of Losses into $S, F, L$ by Friction

*Panel A: Share at Risk, S*




*Panel B: Friction Probability Conditional on Risk, F*

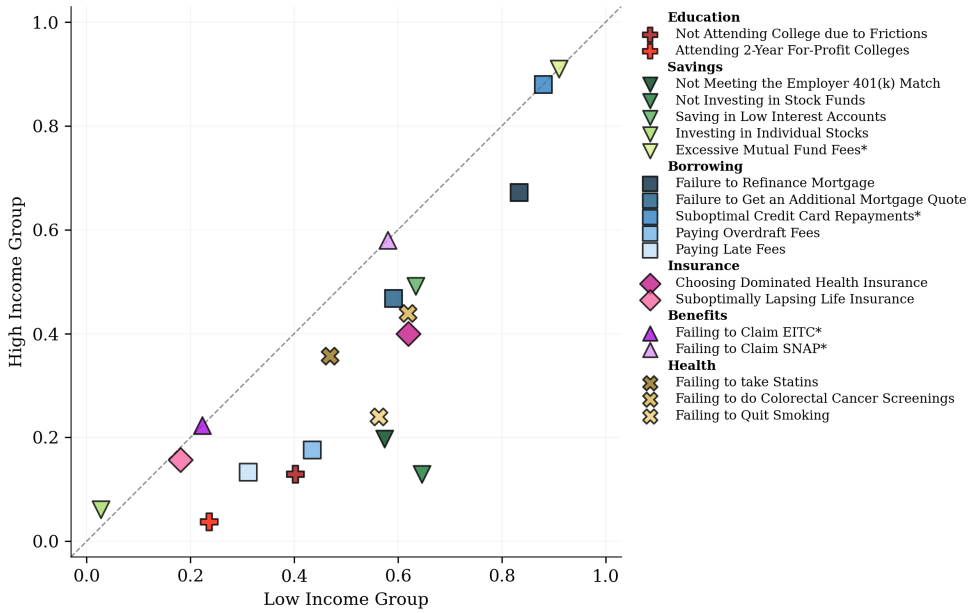
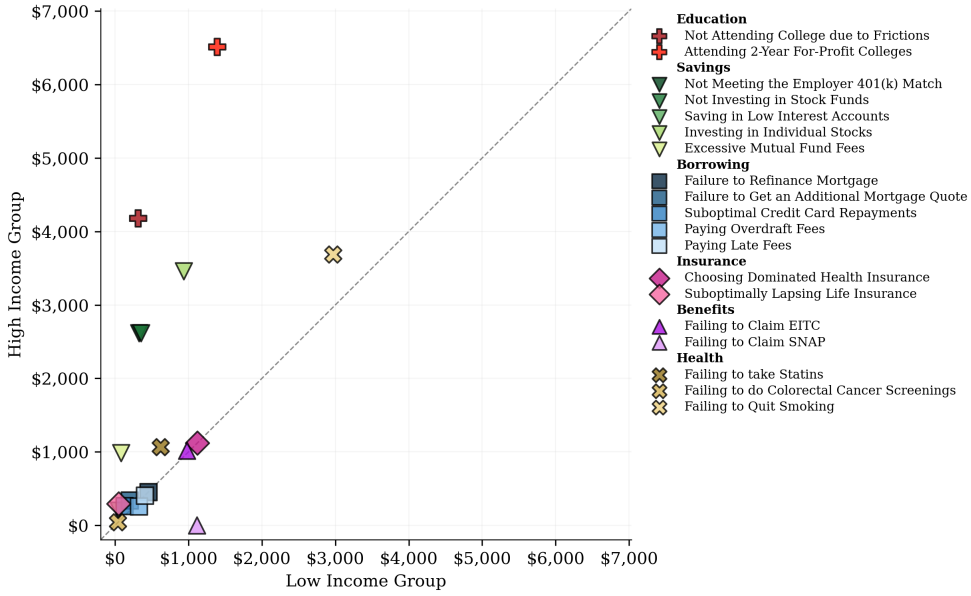
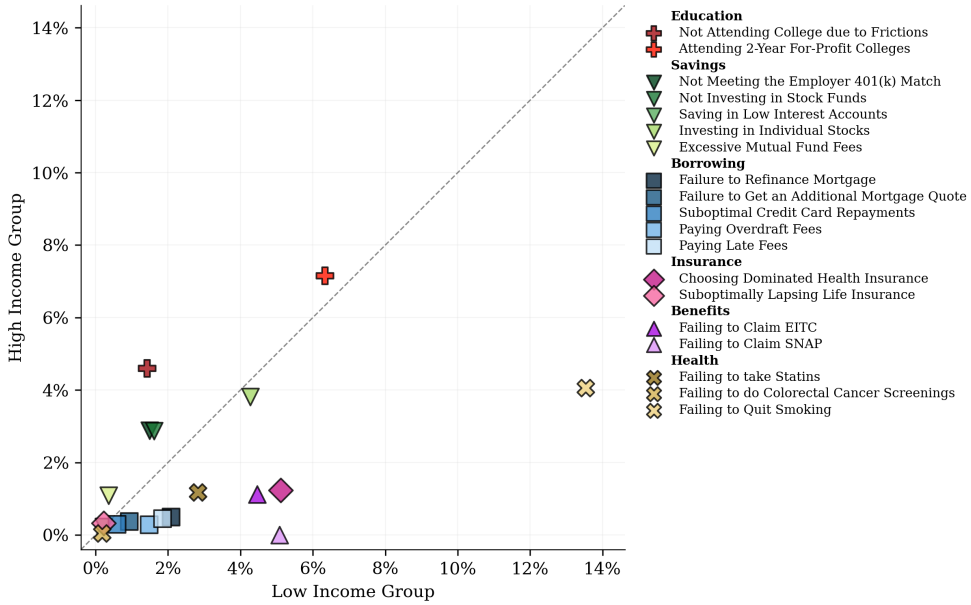


Figure 2: Decomposition of Losses into $S, F, L$ by Friction (Continued)

*Panel C: Loss Conditional on Friction, L*

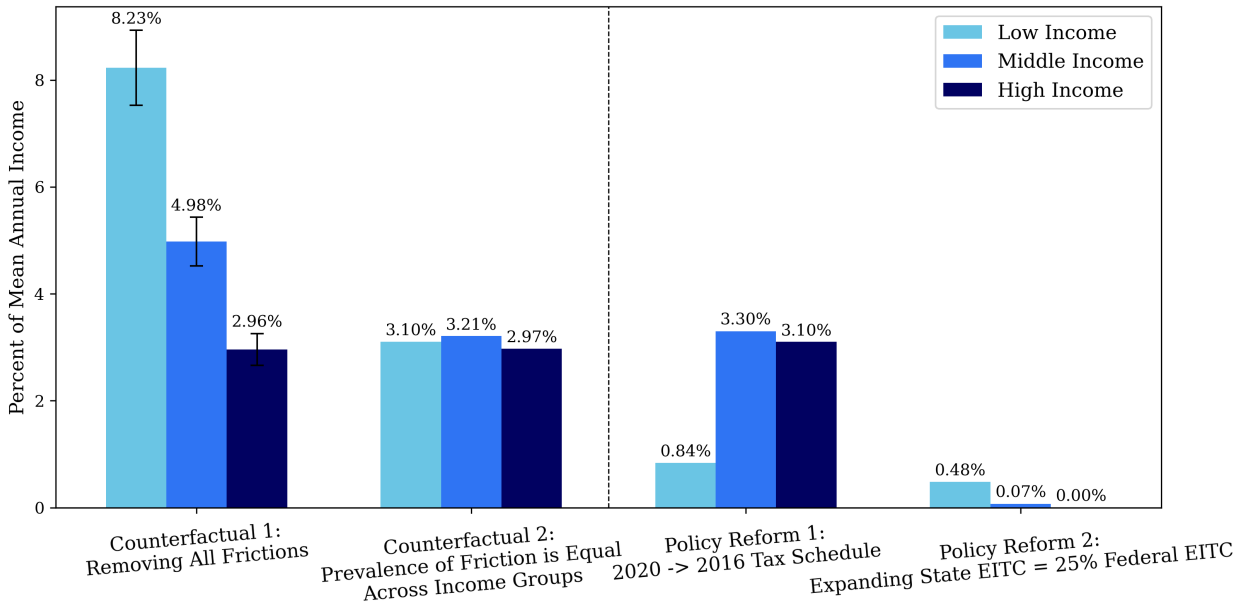



*Panel D: Loss Conditional on Friction as Percentage of Income, L/ y*



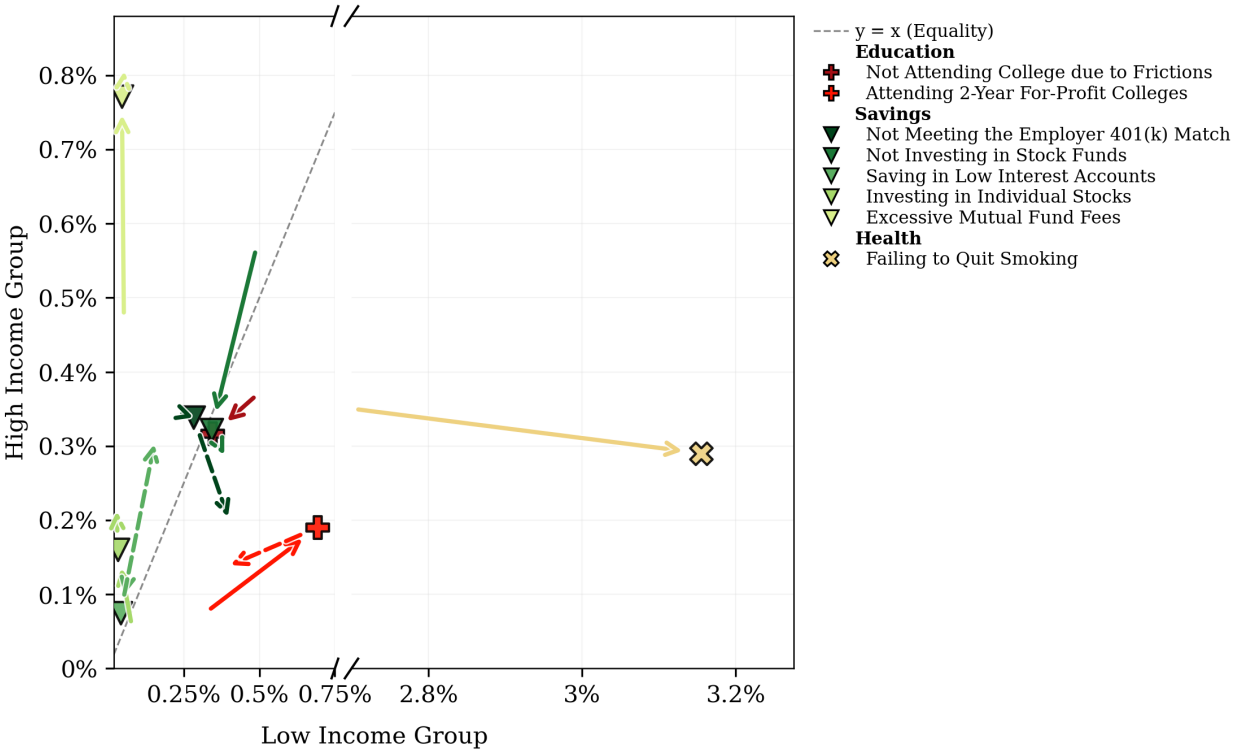

*Notes:* The blue lines indicate the mean of each axis. The asterisk in Panel B indicates frictions where we can not observe the heterogeneity in $F$ by income group.

Figure 3: Percent Counterfactuals




*Notes:*

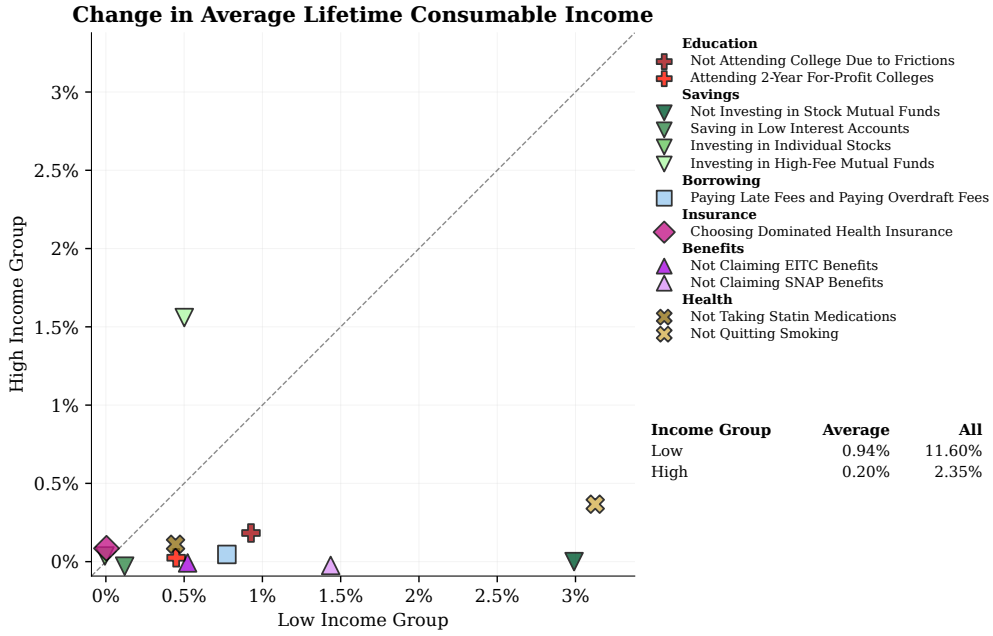
Figure 4: Evolution




*Notes:*

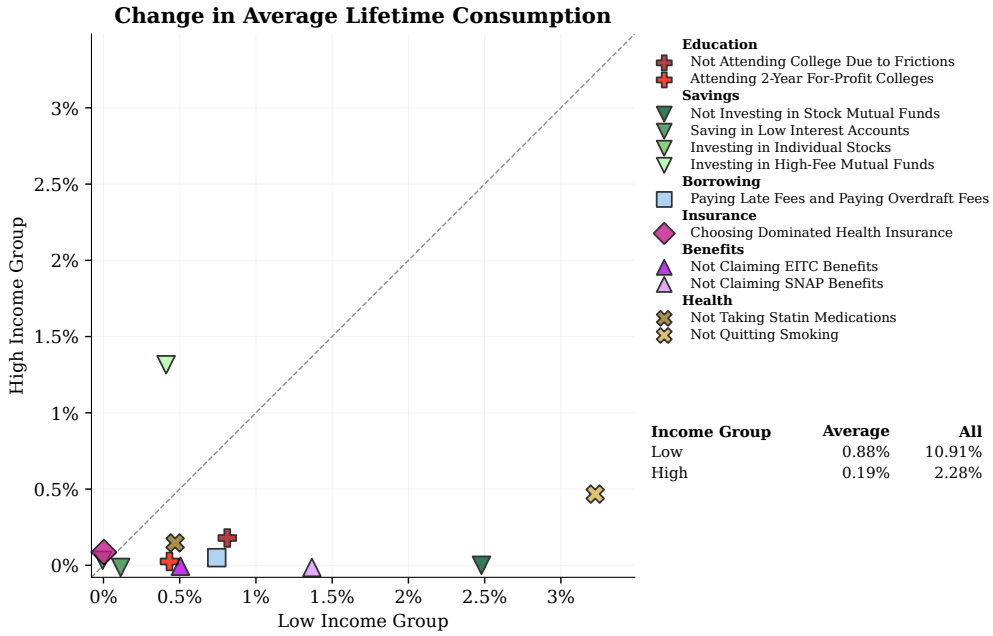
Figure 5: Model Results: Effects of Removing Frictions on Low and High Permanent Income Groups

*Panel A: Change in Average Lifetime Consumable Income,* $\Delta R_{sum}$




| Income Group | Average | All |
|---|---|---|
| Low | 0.94% | 11.60% |
| High | 0.20% | 2.35% |

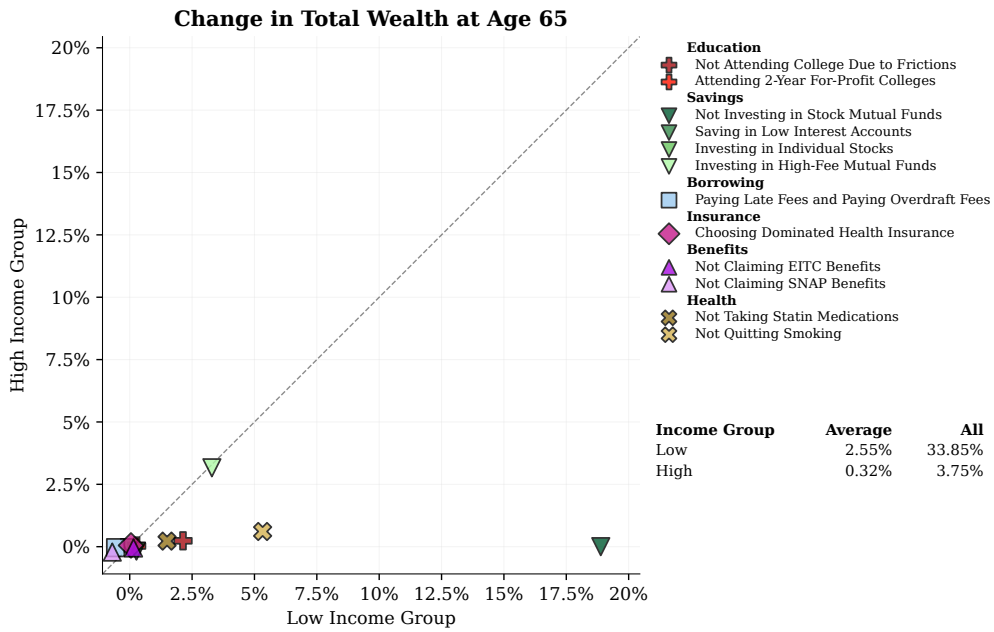
*Panel B: Change in Average Lifetime Consumption,* $\Delta\text{Consumption}_{sum}$




| Income Group | Average | All |
|---|---|---|
| Low | 0.88% | 10.91% |
| High | 0.19% | 2.28% |

Figure 5: Model Results: Effects of Removing Frictions on Low and High Permanent Income Groups (Continued)

*Panel C: Change in Total Wealth Within Income Group at Retirement,* $\Delta \sum \text{Wealth}_{65}$




| Income Group | Average | All |
|---|---|---|
| Low | 2.55% | 33.85% |
| High | 0.32% | 3.75% |

*Notes:* This figure plots the percent impacts reported in Table 6 for the low- and high-income groups. Each point corresponds to one friction with a nonzero impact in at least one of the three plotted outcomes. The x-axis reports the low-income impact and the y-axis reports the high-income impact. The gray dashed line is the 45-degree line. Panel A reports the change in undiscounted lifetime consumable income, Panel B reports the change in undiscounted lifetime consumption, and Panel C reports the change in total age-65 wealth within the permanent income group, assigning zero wealth in a scenario to individuals who are not alive at age 65. The table in the bottom right reports, separately for the low- and high-income groups, the unweighted average across the plotted individual-friction impacts and the impact of turning off all frictions simultaneously.

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# APPENDIX TO

# "BEHAVIORAL INEQUALITY: THE CONTRIBUTION OF DECISION-MAKING FRICTIONS TO INEQUALITY"

**FOR ONLINE PUBLICATION ONLY**

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# Appendix A. Choice of Frictions

We use both the syllabi of undergraduate financial literacy courses offered at top US universities and state learning standards for high school financial literacy courses to determine relevant behavioral frictions. To ensure sufficient detail, we only use syllabi with at least 300 words of relevant information. The included universities are Columbia University, Duke University, Harvard University, Princeton University, Stanford University, University of California, Berkeley, University of California, San Diego, University of Florida, University of North Carolina at Chapel Hill, and Yale University.[1] For the high school syllabi, the included state learning standards are California, Florida, Utah, Pennsylvania, Texas, Ohio, Georgia, Colorado, Rhode Island, and Missouri, covering the four main regions of the U.S. (Northeast, Midwest, South, and West). Multiple undergraduates read each syllabus for potential frictions, compiling a list of potential frictions. They double-check each other's work, determining which frictions are explicitly covered and which ones are not.

Table 1 summarizes the coverage of frictions we chose to include in the paper. Table A1 summarizes the coverage of frictions which appear with some frequency in the syllabi and which for vairous reasons we are not able to to include in the paper, in most cases due to a lack of data and/or prior research (for example, the impact of not building a credit score), and in other cases because the friction is not obviously a behavioral friction (e.g., falling victim to fraud). In general, only a small number of these additional frictions have consistent enough coverage in the syllabi, and these are the ones that we cannot comfortably add to our list. Overall, this suggests to us that we have included in the paper a good share of the personal finance frictions most commonly featured in syllabi.

Table A1: Potential Decision-Making Frictions

| No. | Category | Friction | No. of Syllabi Covering Friction | |
|---|---|---|---|---|
| | | | Top Universities (Out of 10) | High Schools (Out of 10) |
| 1 | Savings | Choosing a Suboptimal Saving Rate | 8 | 10 |
| 2 | Savings | Being Unbanked | 0 | 2 |
| 3 | Savings | Not Contributing to an HSA when Eligible | 2 | 1 |
| 4 | Borrowing | Not Building A Credit Score | 7 | 10 |
| 5 | Borrowing | Not Filing for Bankruptcy When Advantageous | 3 | 2 |
| 6 | Borrowing | Minimizing Educational Debt | 1 | 2 |
| 7 | Borrowing | Using Payday loans and Pawn shops | 3 | 4 |
| 8 | Borrowing | Not Shopping for Cars and Auto Loans | 2 | 0 |
| 9 | Insurance | Purchasing Unnecessary Insurance | 1 | 4 |
| 10 | Insurance | Buying Cash Value Life Insurance | 3 | 1 |
| 11 | Fraud | Falling Victim to Fraud | 1 | 9 |
| 12 | Taxes | Not Filing Taxes | 4 | 7 |

[1] We exclude graduate-level courses at the University of Chicago and Massachussetts Institute of Technology, a course intended for high school students at the University of Pennsylvania, and courses with a low word count syllabi at New York University and the Georgia Institute of Technology.

## Appendix B. Computing Average Consumable Income by Income Group

In this section, we describe how we compute average consumable income—$\bar{R}_j$ defined in (8)—that we use to compute the percent losses from the various frictions. We construct consumable income using (3): adding labor income, capital income, and transfers, and subtracting taxes and direct dollar losses associated with all of the decision-making frictions. We obtain the first four components from the PSID, and we calculate the fifth component as the average direct dollar loss suffered by individuals due to our frictions.

Having computed consumable income, $R_{it}$, at the individual-year level, we now describe how we compute average consumable income, $\bar{R}_j$. In principle, we could simply average the observed values of $R_{it}$ separately within each income group, $j$, which are defined based on current pre-tax pre-transfer income. These values are reported in column (1) of Table B1. However, this approach overstates heterogeneity across groups due to transitory income fluctuations. Therefore, we instead estimate the permanent consumable income of all individuals, and then average these estimates to obtain $\bar{R}_j$.

Table B1: Alternate Measures of Average Income

| Income Group | Average Income at Age | Average Income at Age, Among Individuals with Multiple Observations | Average Income Across All Ages, Among Individuals with Multiple Observations | Average Annual Income per Rafkin et al. (2023) Procedure |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Low | \$18,476 | \$18,207 | \$22,449 | \$21,931 |
| Middle | \$40,834 | \$41,425 | \$42,487 | \$43,262 |
| High | \$96,381 | \$98,523 | \$92,138 | \$90,955 |

We estimate permanent consumable income by applying the empirical Bayes procedure from Appendix B.2. of Rafkin et al. (2023). In summary, this procedure involves estimating a Poisson regression model with individual fixed effects interacted with age-specific coefficients, shrinking the estimated fixed effects to account for sampling variation, and converting the fixed effects into estimates of average annual income over an individual's lifetime. To estimate individual fixed effects, we restrict our sample to individuals who appear at least twice in the PSID; column (2) in Table B1 shows how the estimates in column (1) change with this restriction. Column (4) of Table B1 reports our estimates of the mean of these average annual income estimates within each income group, which correspond to our estimate of the average permanent consumable income. We use these values for $\bar{R}_j$. As validation, column (3) of Table B1 reports a simpler approach that also accounts for transitory income fluctuations, but not sampling variation in which we estimate permanent consumable income, by simply averaging $R_{it}$ across all ages for which an individual is observed, before taking the mean across all individuals in each income group. The results are quantitatively similar to the column (4).

In Table B2, we decompose consumable income into its various components. While we are not able to decompose the values in column (4) of Table B1, we instead decompose column (3). The share of income coming from labor income and capital income rises across income groups, while both the share of income coming from

Table B2: Decomposition of Consumable Income from Column 2 in Table B1

| Income Source | Low Income | Middle Income | High Income |
|---|---|---|---|
| Labor Income | 53.7% | 88.0% | 102.1% |
| Capital Income | −2.7% | 3.9% | 14.9% |
| Social Security | 19.7% | 12.8% | 8.2% |
| Other Transfers | 34.4% | 12.6% | 8.4% |
| Taxes | −3.6% | −16.3% | −33.1% |
| Loss from (Subset of) Frictions | −1.4% | −1.0% | −0.5% |

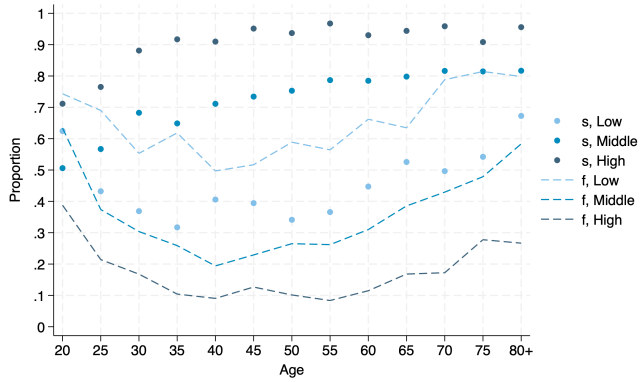
government transfers and the share of income lost due to taxes decrease across income groups. The share of income directly lost due to decision-making frictions in our baseline is low. Importantly, this only includes frictions that create direct dollar losses, as opposed to affecting earnings. Table 3 indicates the total savings possible if all frictions were to be alleviated.

# Appendix C. $S$ and $F$ Figures

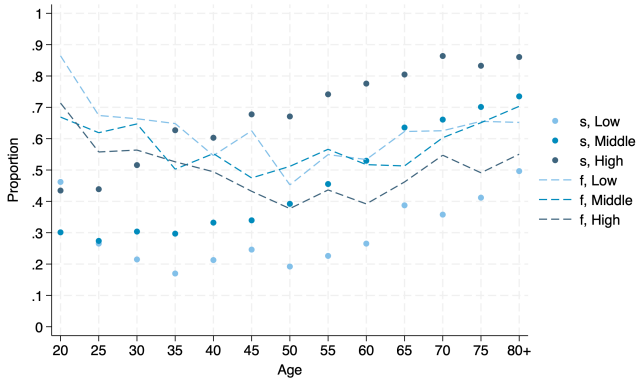
The following figures display for most of the behavioral frictions the estimates for $S_j$ and for $F_j$ as a function of the age of the consumer, in 5-year bins.

Figure C1: Empirical Evidence of all Frictions

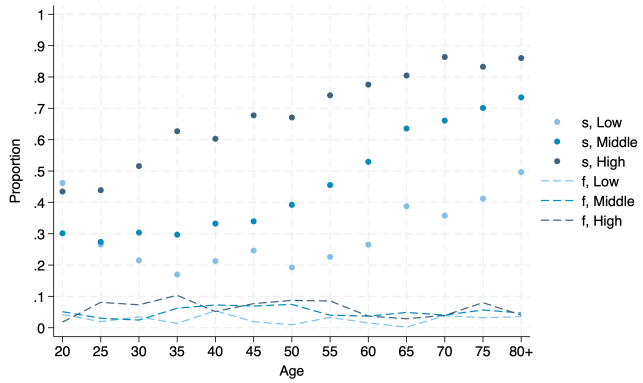
(a) Panel A: Not Investing in Stock Mutual Funds




(b) Panel B: Saving in Low Interest Accounts




(c) Panel C: Investing in Individual Stocks




(d) Panel D: Investing in High-Fee Mutual Funds

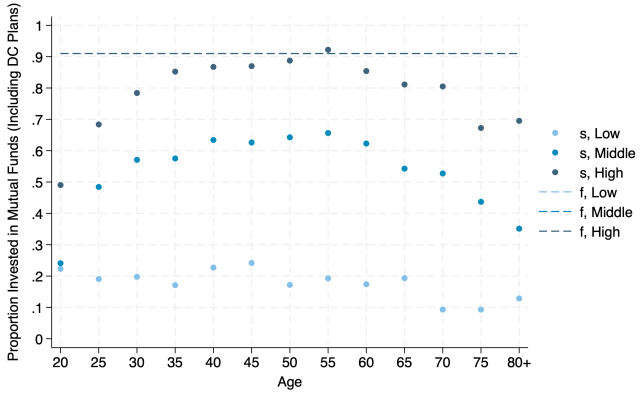
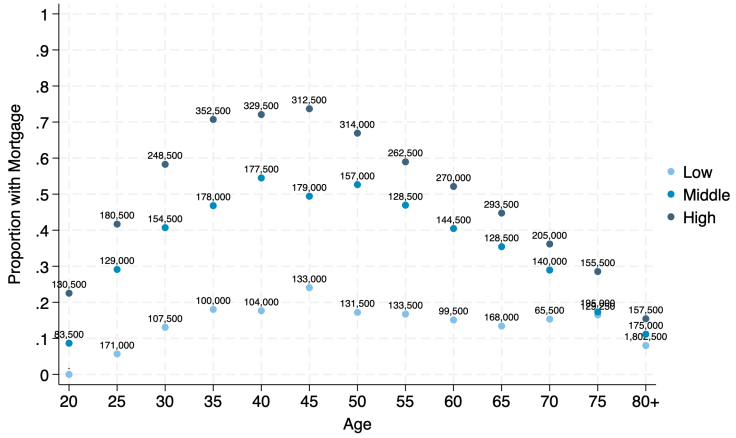
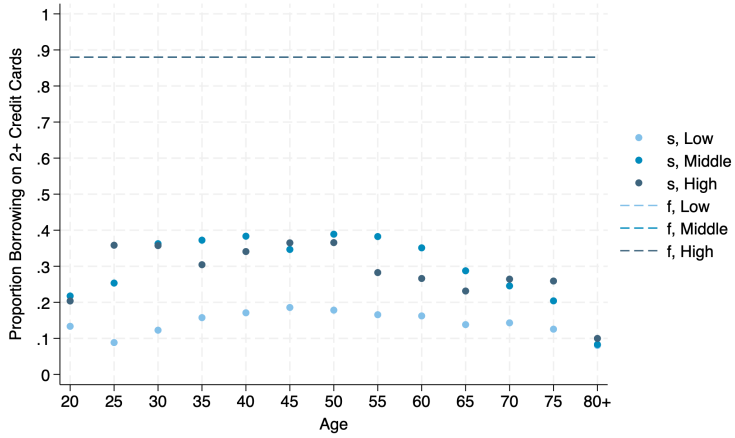


Figure C1: Empirical Evidence of all Frictions (Continued)

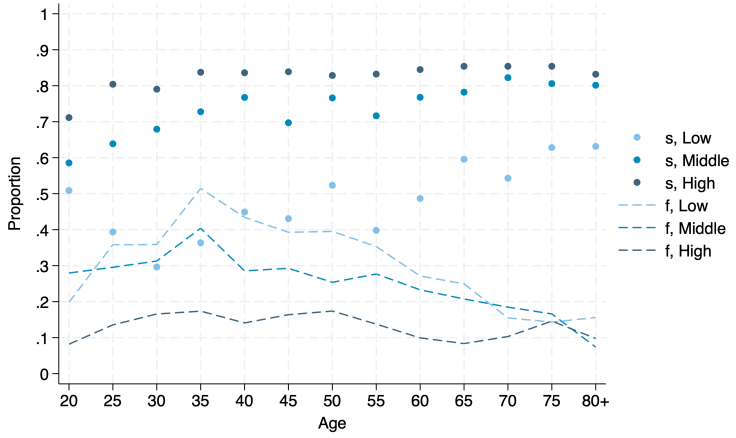
(e) Panel E: Not Refinancing a Mortgage




(f) Panel F: Suboptimally Repaying Credit Card Debt




(g) Panel G: Paying Late Fees




(h) Panel H: Paying Overdraft Fees

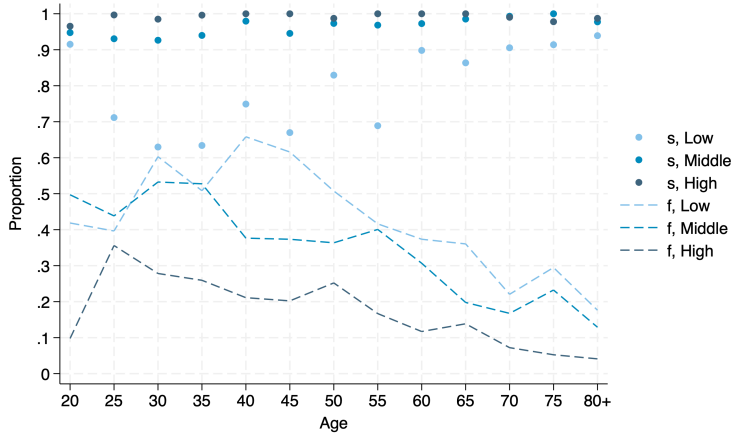
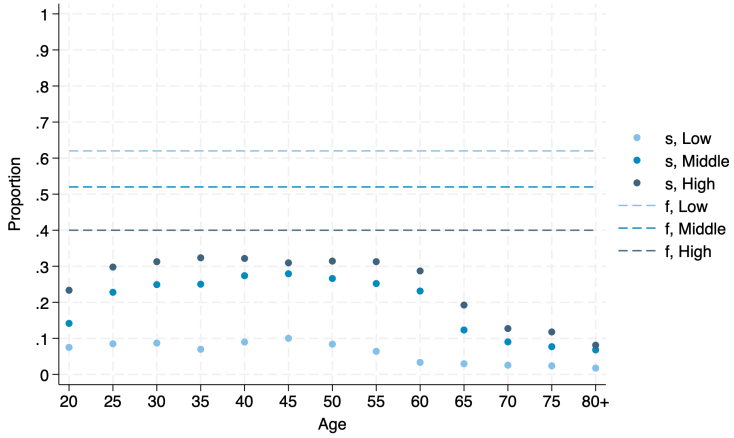
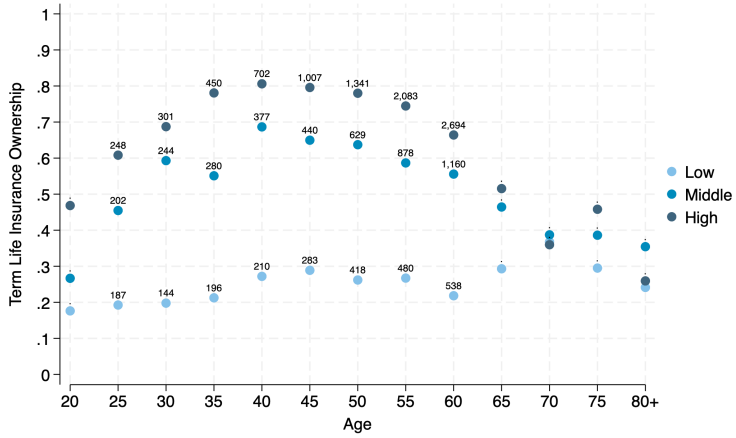


Figure C1: Empirical Evidence of all Frictions (Continued)

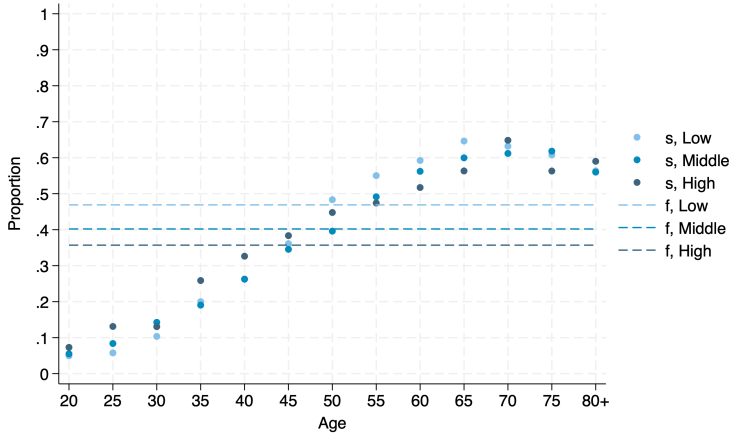
(i) Panel I: Choosing Dominated Health Insurance



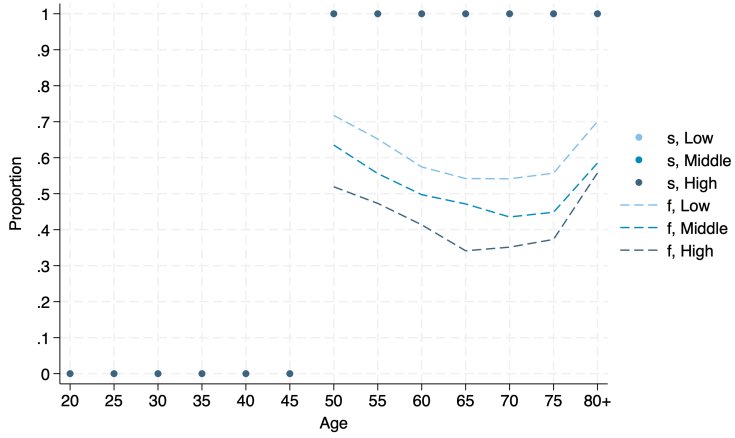

(j) Panel J: Suboptimally Lapsing Life Insurance




(k) Panel K: Not Taking Statin Medications




(l) Panel L: Not Screening for Colon Cancer



## Appendix D. Evolution of Frictions from late 1990s to 2010s to 2020s

Table D1: Change in Frictions, from 1995-2005 to 2010-2020 to 2020-2025

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions (2000 → 2016)* | | | | |
| Low Income | 0.503 → 0.346 | 0.552 | \$368 → \$399 | \$102 → \$76 |
| Middle Income | 0.405 → 0.350 | 0.384 | \$2,344 → \$2,501 | \$365 → \$336 |
| High Income | 0.231 → 0.175 | 0.361 | \$3,853 → \$4,562 | \$321 → \$288 |
| *Panel B: Attending 2-Year For-Profit Colleges (1996-2001 → 2012-2017 → 2020-2022)* | | | | |
| Low Income | 0.279 → 0.348 → 0.300 | 0.149 → 0.231 → 0.142 | \$1,738 → \$1,884 → \$2,301 | \$72 → \$152 → \$98 |
| Middle Income | 0.295 → 0.322 → 0.246 | 0.091 → 0.138 → 0.108 | \$4,424 → \$4,720 → \$5,287 | \$119 → \$210 → \$140 |
| High Income | 0.259 → 0.262 → 0.203 | 0.045 → 0.091 → 0.085 | \$6,117 → \$7,242 → \$8,117 | \$71 → \$173 → \$140 |
| *Panel C: Not Meeting the Employer 401(k) Match (1998 → 2020 → 2025)* | | | | |
| Low Income | 0.219 → 0.292 → 0.337 | 0.663 → 0.572 → 0.612 | \$382 → \$395 → \$494 | \$56 → \$66 → \$102 |
| Middle Income | 0.331 → 0.462 → 0.483 | 0.402 → 0.299 → 0.325 | \$1,446 → \$1,438 → \$1,635 | \$192 → \$199 → \$256 |
| High Income | 0.413 → 0.517 → 0.528 | 0.261 → 0.197 → 0.136 | \$2,475 → \$2,677 → \$2,482 | \$266 → \$272 → \$178 |
| *Panel D: Not Investing in Stock Mutual Funds (1998-2004 → 2013-2019 → 2022)* | | | | |
| Low Income | 0.369 → 0.327 → 0.340 | 0.661 → 0.646 → 0.581 | \$422 → \$354 → \$470 | \$103 → \$75 → \$93 |
| Middle Income | 0.692 → 0.643 → 0.706 | 0.389 → 0.305 → 0.249 | \$870 → \$959 → \$994 | \$235 → \$188 → \$174 |
| High Income | 0.873 → 0.867 → 0.888 | 0.205 → 0.129 → 0.083 | \$2,756 → \$2,615 → \$3,924 | \$493 → \$293 → \$289 |
| *Panel E: Saving in Low Interest Accounts (1998-2004 → 2013-2019 → 2022)* | | | | |

Continued on next page

Table D1 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| Low Income | 0.327 → 0.282 → 0.289 | 0.621 → 0.634 → 0.637 | \$61 → \$48 → \$202 | \$12 → \$9 → \$37 |
| Middle Income | 0.559 → 0.451 → 0.518 | 0.555 → 0.582 → 0.645 | \$125 → \$97 → \$294 | \$39 → \$26 → \$98 |
| High Income | 0.753 → 0.686 → 0.749 | 0.492 → 0.491 → 0.535 | \$251 → \$202 → \$760 | \$93 → \$68 → \$304 |
| *Panel F: Investing in Individual Stocks (1998-2004 → 2013-2019 → 2022)* | | | | |
| Low Income | 0.327 → 0.282 → 0.289 | 0.038 → 0.027 → 0.017 | \$1,333 → \$937 → \$1,382 | \$16 → \$7 → \$7 |
| Middle Income | 0.559 → 0.451 → 0.518 | 0.056 → 0.050 → 0.026 | \$1,007 → \$1,445 → \$1,019 | \$31 → \$32 → \$14 |
| High Income | 0.753 → 0.686 → 0.749 | 0.071 → 0.062 → 0.049 | \$1,056 → \$3,449 → \$5,787 | \$56 → \$146 → \$213 |
| *Panel G: Investing in High-Fee Mutual Funds (1998-2004 → 2013-2019 → 2022)* | | | | |
| Low Income | 0.145 → 0.136 → 0.164 | 0.910 | \$81 → \$79 → \$87 | \$11 → \$10 → \$13 |
| Middle Income | 0.467 → 0.498 → 0.564 | 0.910 | \$171 → \$168 → \$153 | \$73 → \$76 → \$79 |
| High Income | 0.716 → 0.781 → 0.847 | 0.910 | \$647 → \$987 → \$1,050 | \$422 → \$702 → \$809 |
| *Panel H: Suboptimal Credit Card Repayments (1998-2004 → 2013-2019 → 2022)* | | | | |
| Low Income | 0.161 → 0.144 → 0.247 | 0.880 | \$97 → \$129 → \$106 | \$14 → \$16 → \$23 |
| Middle Income | 0.289 → 0.305 → 0.387 | 0.880 | \$125 → \$177 → \$160 | \$32 → \$47 → \$54 |
| High Income | 0.284 → 0.285 → 0.265 | 0.880 | \$182 → \$263 → \$210 | \$45 → \$66 → \$49 |
| *Panel I: Failing to Quit Smoking (1997-2005 → 2010-2018)* | | | | |
| Low Income<br>*Health*<br>*Monetary* | 0.209 → 0.202 | 0.591 → 0.563 | \$4,647 → \$5,595<br>\$3,674 → \$3,982<br>\$973 → \$1,613 | \$574 → \$638<br>\$454 → \$454<br>\$120 → \$184 |
| Middle Income | 0.229 → 0.188 | 0.346 → 0.414 | \$7,050 → \$8,087 | \$557 → \$628 |

Continued on next page

Table D1 – continued from previous page

| Income Group ($j$) | $S_j$ | $F_j$ | $L_j$ | $S_j \cdot F_j \cdot L_j$ |
|---|---|---|---|---|
| *Health* | | | \$6,096 → \$6,504 | \$482 → \$505 |
| *Monetary* | | | \$954 → \$1,583 | \$75 → \$123 |
| High Income | 0.245 → 0.168 | 0.251 → 0.240 | \$7,115 → \$8,816 | \$437 → \$355 |
| *Health* | | | \$6,290 → \$7,447 | \$387 → \$300 |
| *Monetary* | | | \$825 → \$1,369 | \$51 → \$55 |

*Notes:* For the mortgage refinancing friction, $F_j$ is modeled as an i.i.d. friction across the years, as opposed to assuming that a fixed fraction of individuals have a persistent friction. So, our estimates for $L_j$ already implicitly incorporate the probability of checking for refinancing. For all other frictions, $F_j$ is the annual probability of committing the friction, assuming perfect auto-correlation in who commits the frictions across years, and $L_j$ is the average loss conditional on committing the friction.

# Appendix E. Education Frictions

## E.1 Not Attending College Due to Frictions

**Suggestive Evidence for the Friction.** We report here suggestive evidence about frictions to attending college for low-income students. Ma and Pender (2023) show that even conditioning on PSAT quartile there is a difference of 10 percentage points or higher in college attendance between the lower neighborhood income group and the higher neighborhood income group. Table E1 provides further evidence, showing college attendance by parental income group after controlling for grades, math scores, and various controls.

Table E1: College Attendance Regressions

| | Attending Any College | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Intercept | $0.592^{***}$ | | |
| | (0.015) | | |
| Middle Parental Income (32%-75%) | $0.150^{***}$ | $0.048^{***}$ | $0.068^{***}$ |
| | (0.019) | (0.017) | (0.017) |
| High Parental Income (75%+) | $0.302^{***}$ | $0.127^{***}$ | $0.159^{***}$ |
| | (0.017) | (0.015) | (0.015) |
| Academic GPA FE | | ✓ | ✓ |
| Math Cognitive Test FE | | ✓ | ✓ |
| School FE | | | ✓ |
| Sex FE | | | ✓ |
| Race FE | | | ✓ |
| Observations | 12210 | 12210 | 12210 |
| $R^2$ | 0.082 | 0.270 | 0.280 |

*Notes:* We use the 2009 High School Longitudinal Survey (HSLS) to regress attending any college on parental income groups, controlling for academic ability and demographic fixed effects.

**Construction of $(S_j)$ and $(F_j)$.** Throughout the analysis, we divide students into the bottom 20 percent, middle 60 percent, and top 20 percent of the parental-income distribution. We estimate $(S_j)$, the share of income group (j) not attending college, as $(S_j = 1 - p_j^{\text{college}})$, where $(p_j^{\text{college}})$ is the college-enrollment rate reported by Snyder et al. (2019). We use the moving-average enrollment rates rather than the single-year estimates because the latter are particularly noisy when disaggregated by income. Since subtracting the enrollment rate from one does not change its variance, the standard error of $(S_j)$ equals the reported standard error of the enrollment estimate after converting it from percentage points to a proportion.

**Measuring Additional Debt and Lost Earnings.** To measure loss $L$ due to not attending college, we assume it to be 12 percent of life-time earnings, as well as extra debt and lost earnings. To measure the extra debt and the lost earnings, we use data from the one paper in the literature with direct evidence on these variables, Mountjoy (2025),

finding that the estimated extra debt is \$5,277 and lost earnings is \$4,000. Inflating to 2020 dollars, for individuals affected by this friction in our model, we increase their student loans from \$0 to \$5,762, and we subtract \$4,368 times the marginal propensity to save, 0.6, from their starting wealth.

**Evolution Over Time.** We track the proportion of high schoolers attending college in the year 2000 using Snyder et al. (2019). Table D1 tracks how $S_j$ evolves from the year 2000 to 2016 by income group. Lacking additional information, we assume that $F_j$ and $L_j$ are constant over time, only adjusting $L_j$ by wage inflation (using estimates provided by the Economic Policy Institute (2026)), and compute the implied change in $S_j \cdot F_j \cdot L_j$.

**Confidence Intervals.** We obtain the uncertainty in $(S_j)$ from the standard errors of the college-enrollment estimates reported by Snyder et al. (2019). To estimate uncertainty in $(F_j)$, we use a parametric bootstrap. In each iteration, we draw the effect of each intervention from its reported sampling distribution and combine the draws using the assumed correlation of 0.032 to construct $(T_j)$. We independently draw $(S_{\text{low}})$ from its estimated sampling distribution and calculate $(F_j = T_j / S_{\text{low}})$. The same draw of $(S_{\text{low}})$ is used for all three income groups within an iteration because it is their common denominator. We draw the intervention effects and $(S_{\text{low}})$ independently because they are estimated from unrelated samples.

To capture uncertainty in $(L_j)$, we additionally draw the earnings return to attending college from the distribution implied by the four regression-discontinuity estimates and recompute the lifecycle-model loss, including the effects on earnings, student debt, initial wealth, and retirement income. In each iteration, we then calculate $(S_j F_j L_j = S_j (T_j / S_{\text{low}}) L_j)$. We report bootstrap standard errors and 95 percent percentile confidence intervals based on the 2.5th and 97.5th percentiles of the resulting bootstrap distributions.

**Model Implementation.** In the model, we calibrate the proportion of people in each income x education group and their income levels using the PSID. This gives us a slightly different proportion of people who attend any college relative to Table 3: while the estimates for $S$ in Table 3 are 0.497, 0.351, and 0.196, the corresponding estimates using the PSID are 0.477, 0.225, and 0.064. Our estimates of $S$ differ from those of the PSID because i) the PSID proportions are calculated from a sample of 22-65 year olds, while Snyder et al. (2019) and BPS (2017) both draw from recent high schoolers, and ii) the PSID sorts people based on permanent income groups, while our estimates rely on parental income. We first proportionally alter the estimates of $F$ to preserve the overall $S \cdot F$ in Table 3. Specifically, for each parental-income group $j$, we calculate $F_j^{P,m} = F_j^{\text{Table 3}} S_j^{\text{Table 3}} / S_j^{\text{PSID}}$. This gives values of $F_j^{P,m}$ equal to 0.419, 0.434, and 0.395 for the low-, middle-, and high-parental-income groups, respectively. We then translate these values to child permanent-income groups using the intergenerational income correlation of 0.5 estimated by Guvenen et al. (2024, Table II and equation (15)). We simulate correlated Gaussian parental and child latent incomes, divide parental income into the 20–60–20 groups used in our empirical estimates and child income according to the model's permanent-income-group shares, and calculate $T_{kj} = \Pr(P = j \mid C = k)$. The model prevalence for child permanent-income group $k$ is $F_k^{C,m} = \sum_j T_{kj} F_j^{P,m}$. This gives final model values of $F$ equal to 0.426, 0.425, and 0.418 for the low-, middle-, and high-child-income groups, respectively.

## E.2 Attending 2-Year For-Profit Colleges

Table E2 summarizes our estimates of 2-year college attendance by parental income group.

**Construction of $(S_j)$ and $(F_j)$.** We combine overall college-enrollment rates from Snyder et al. (2019) with conditional institution-type shares from the Beginning Postsecondary Students Longitudinal Study (BPS, 2017). The income groups are the bottom 20 percent, middle 60 percent, and top 20 percent of the weighted parental-income distribution among dependent BPS students. The restriction to dependent students arises because the parental-income variables are defined only for these respondents.

Let $(A_j)$ denote the probability of attending any college, $(C_j)$ the probability of attending a for-profit program of two years or less conditional on attending college, and $(D_j)$ the corresponding probability of attending a public or nonprofit program. We calculate $(S_j = A_j(C_j + D_j))$, so that $(S_j)$ is the unconditional share of income group $(j)$ attending a program of two years or less. We calculate $(F_j = C_j/(C_j + D_j))$, so that $(F_j)$ is the share of such attendance occurring at for-profit institutions.

For example, Snyder et al. (2019) report that 65.4% of low-income students attend college, while BPS (2017) report that, conditional on attending college, 6.9% attend a private two-year for-profit institution and 5.4% attend a private less-than-two-year for-profit institution. We therefore estimate that (0.654(6.9+5.4)/100=0.080), or 8.0%, of low-income students attend a for-profit program of two years or less.

Table E2: Student College Attendance Proportions by Income Level

| Parental Income Group | Attendance by Institution Type (Snyder et al. (2019); BPS (2017)) | | | |
|---|---|---|---|---|
| | 2-Year For-Profit | 2-Year Public or Non-Profit | $\mathbb{P}$(For-Profit \| 2-Year) | 4-Year |
| | (1) | (2) | (3) | (4) |
| Low | 0.080 | 0.267 | 0.231 | 0.306 |
| Middle | 0.045 | 0.277 | 0.138 | 0.329 |
| High | 0.024 | 0.238 | 0.091 | 0.562 |

**Confidence Intervals.** We obtain standard errors for $(S_j)$ and $(F_j)$ using a parametric bootstrap. In each iteration, we draw the overall college-enrollment probability $(A_j)$ from the sampling distribution implied by the standard error reported by Snyder et al. (2019). We also draw the conditional for-profit and public or nonprofit attendance shares, $(C_j)$ and $(D_j)$, from the sampling distributions reported by the BPS. We then calculate $(S_j = A_j(C_j + D_j))$ and $(F_j = C_j/(C_j + D_j))$. We treat the sampling errors of $(A_j)$, $(C_j)$, and $(D_j)$ as independent. In particular, the independence of $(C_j)$ and $(D_j)$ is an approximation necessitated by the absence of their estimated covariance.

To capture uncertainty in $(L_j)$, we draw the for-profit earnings penalty and employment effect from the sampling distributions estimated by Cellini and Turner (2019) and recompute the model counterfactual while holding the underlying simulated individuals and income and employment shocks fixed. In each iteration, we calculate the total effect as $(S_j F_j L_j)$. We report bootstrap standard errors and 95 percent percentile confidence intervals

based on the 2.5th and 97.5th percentiles of the bootstrap distributions.

**Evolution Over Time.** We track the proportion of high schoolers attending college in the year 2000 using Snyder et al. (2019), and the proportion of high schoolers attending 2-year for-profit colleges conditional on college attendance from the 1996/2001 and the 2020/2022 BPS surveys. Snyder et al. (2019) does not include information on how college attendance has evolved in the 2020s, so we assume that the overall college attendance rate was constant from 2016 to the 2020s (although we capture the change in for-profit college attendance rate using the newer waves of the BPS surveys). Table D1 tracks how $S_j$ and $F_j$ evolve from the late 1990s/early 2000s to the mid 2010s to the early 2020s. Lacking additional information, we assume that $L_j$ is constant over time, only adjusting the foregone earnings by wage inflation (using estimates provided by the Economic Policy Institute (2026)), and compute the implied change in $S_j \cdot F_j \cdot L_j$.

**Model Implementation.** In the model, we calibrate the proportion of people in each income x education group and their income levels using the PSID. This gives us a slightly different proportion of people who attend any 2-year college relative to Table 3: while the estimates for $S$ in Table 3 are 0.263, 0.277, and 0.138, the corresponding estimates using the PSID are 0.298, 0.323, and 0.112. Our estimates of $S$ differ from those of the PSID because i) the PSID proportions are calculated from a sample of 22-65 year olds, while Snyder et al. (2019) and BPS (2017) both draw from recent high schoolers, and ii) the PSID sorts people based on permanent income groups, while our estimates rely on parental income. We first apply the same proportional adjustment as for the college-attendance friction, preserving $S \cdot F$. This gives values of $F_j^{P,m}$ equal to 0.208, 0.081, and 0.046 for the low-, middle-, and high-parental-income groups, respectively. Applying the same intergenerational transition matrix gives final model values of $F$ equal to 0.133, 0.098, and 0.073 for the low-, middle-, and high-child-income groups, respectively. An important caveat to this procedure is that we assume that the rate of college completion is similar among those who attend for-profit versus other colleges (allowing us to translate the empirical data on proportion of people who attend 2-year for-profit colleges to the model data on the proportion of people who graduate from 2-year for-profit colleges), which may not be true.

# Appendix F. Savings Frictions

## F.1 Not Meeting the Employer 401(k) Match

**No vs Partial Participation.** Bureau of Labor Statistics (2020a) provides us with the proportion of people participating (i.e., making any contributions, not necessarily meeting the full match) in a DC plan, conditional on having access. Carranza et al. (2026) provides us with the share taking up the full employer match, conditional on having access to a DC plan. We divide the proportion of people who don't participate in the DC plan by the proportion of people who don't take up the full employer match to determine the proportion of people with zero contributions to their DC plan. These constitute 83% of low-income, 80% of middle-income and 65% of high-income individuals

affected by the friction. All other people affected by the friction make some contributions to their plan but don't meet the full employer match. Lacking additional information, we assume they contribute 1.5% of their pre-tax income to their plan, enjoying half the maximum employer match.

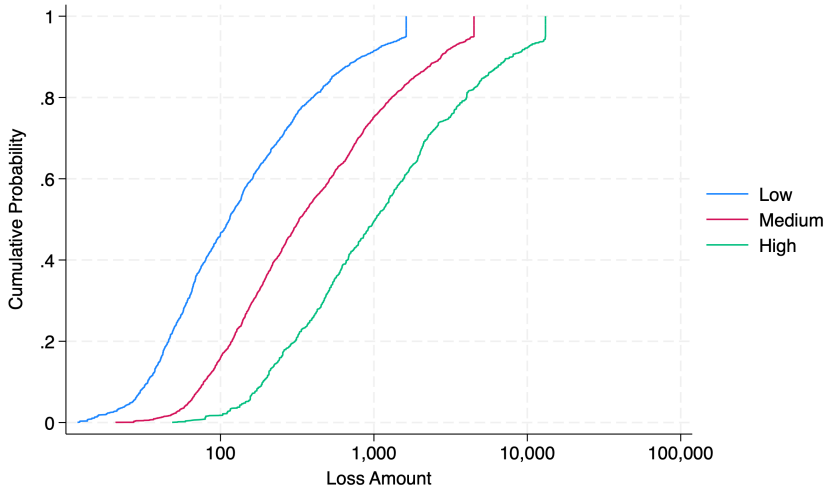
**Confidence Intervals.** We use the confidence intervals provided by Bureau of Labor Statistics (2020b) for 401(k) access ($S$), and as Carranza et al. (2026) for 401(k) participation ($F$). To determine the standard error on the proportion of people missing the entire 3% match, we use the delta method to combine the standard errors of the proportion of people missing the full 401(k) match in Carranza et al. (2026) and the proportion of people not participating in the 401k at all from Bureau of Labor Statistics (2020a). We use the bootstrap method, resampling $S$, $F$, and the proportion of people missing the full employer match, to determine the confidence intervals for $L$ and $SFL$.

**Evolution Over Time.** Purcell (2009) and U.S. Bureau of Labor Statistics (2025) provide statistics on DC Access and Participation in 1998 and 2025 respectively. Deflating their estimates of DC Access to account for unemployed and retired workers, Table D1 shows the evolution in $S_j$ over time. Lacking additional information, we assume $F_j$ and $L_j$ are constant over time, only adjusting the foregone earnings by wage inflation (using estimates provided by the Economic Policy Institute (2026)). We then computed the implied change in the evolution of $S_j \cdot F_j \cdot L_j$.

## F.2 Not Investing in Stock Mutual Funds

**CDF of Losses Due to Not Investing in Stock Mutual Funds.** Figure F1 plots the CDF of losses faced by individuals in the SCF due to not investing, winsorizing the losses at the 95th percentile in each income group.

Figure F1: CDF of Losses Due to Not Investing in Stock Mutual Funds




*Notes:* We plot the CDF of the annual losses due to not investing, winsorized at the 95th percentile.

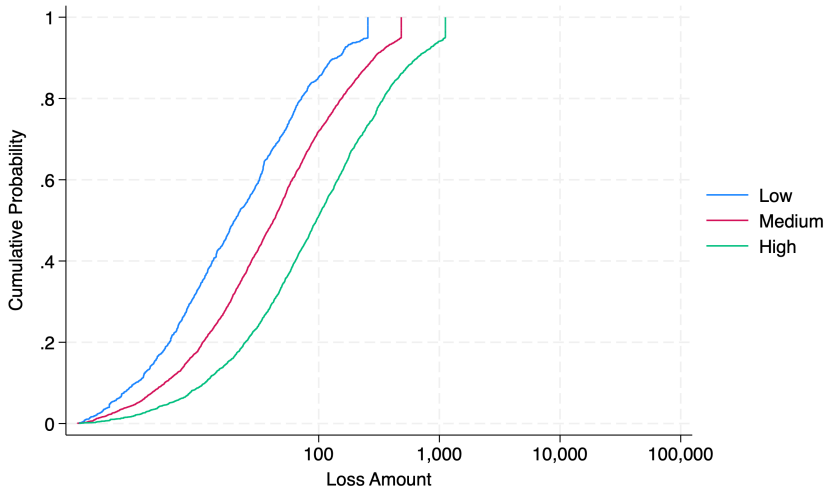
**Confidence Intervals.** We construct confidence intervals for the not investing friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Evolution Over Time.** We use the 1998-2004, 2013-2019, and 2022 waves of the SCF to track the evolution of the friction over time, presenting the results in Table D1.

## F.3 Saving in Low Interest Accounts

**CDF of Losses Due to Saving in Low Interest Accounts.** Figure F2 plots the CDF of losses faced by individuals in the SCF due to not investing, winsorizing the losses at the 95th percentile in each income group.

Figure F2: CDF of Losses Due to Saving in Low Interest Accounts




*Notes:* We plot the CDF of the annual losses due to low-interest checking and savings accounts, winsorized at the 95th percentile.

**Confidence Intervals.** We construct confidence intervals for the low-interest checking and savings accounts friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Evolution Over Time.** We use the 1998-2004, 2013-2019, and 2022 waves of the SCF to track the evolution of the friction over time, presenting the results in Table D1. For each time period, we appropriately adjust our estimates of increased returns due to money market funds per The U.S. Federal Reserve (2026), finding that consumers would

enjoy an average return of around 1.45 percentage points in 1998-2004, 0.74 percentage points in 2013-2019, 1.67 in the early 2020s.

## F.4 Investing in Individual Stocks

**Investing in Individual Stocks Loss Derivation.** Assume an individual holds an equally weighted portfolio of $N$ individual stocks drawn at random from the market. Let $r_i$ denote the (excess) return on stock $i$ over the relevant horizon and let $r_m$ denote the market (excess) return with variance $\sigma_m^2 \equiv \text{Var}(r_m)$. Define $\sigma^2 \equiv \mathbb{E}[\text{Var}(r_i)]$ as the average individual-stock return variance and $\rho \equiv \mathbb{E}[\text{Cov}(r_i, r_j)]$ as the average pairwise covariance for $i \neq j$. The equal-weight portfolio return is $r_p = \frac{1}{N}\sum_{i=1}^{N} r_i$, so

$$\sigma_{ud}^2 \equiv \text{Var}(r_p) = \frac{1}{N^2}\Big(\sum_{i=1}^{N}\text{Var}(r_i) + \sum_{i\neq j}\text{Cov}(r_i, r_j)\Big) \approx \frac{\sigma^2}{N} + \frac{N-1}{N}\rho.$$

Under the CAPM, $r_i = \beta_i r_m + \varepsilon_i$ with $\text{Cov}(\varepsilon_i, \varepsilon_j) = 0$. Therefore, for $i \neq j$, we have $\rho = \mathbb{E}[\beta_i \beta_j]\sigma_m^2$ and for a random draw with $\mathbb{E}[\beta_i] = 1$ (hence $\mathbb{E}[\beta_i \beta_j] \approx 1$), it follows that

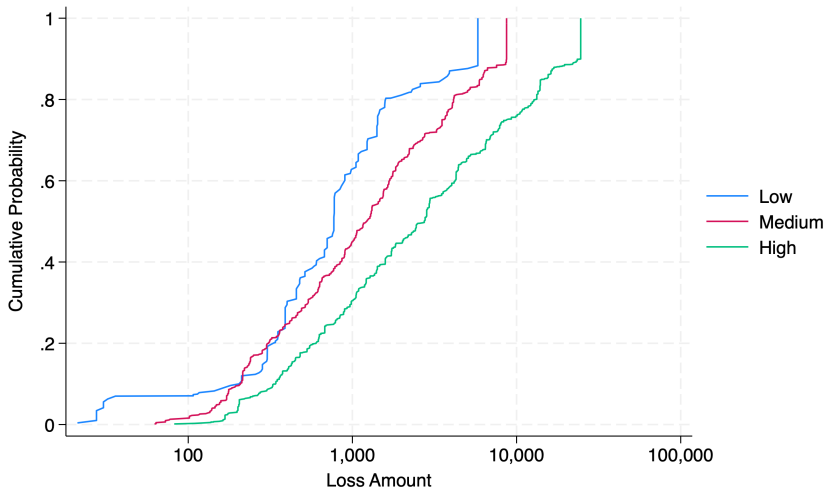
$$\sigma_{ud}^2 \approx \sigma_m^2 + \frac{\sigma^2 - \sigma_m^2}{N}, \qquad L_v \equiv \sigma_{ud}^2 - \sigma_m^2 = \frac{\sigma^2 - \sigma_m^2}{N}.$$

We estimate $\sigma^2 - \sigma_m^2 = 0.07468$ using Campbell et al. (2001).

Using the Arrow–Pratt approximation for multiplicative risks with coefficient of relative risk aversion $\gamma$, the utility cost of the incremental variance $L_v$ is equivalent to a reduction in certainty-equivalent expected return on total wealth of $L_r \equiv \frac{\gamma}{2}\left(\frac{H}{W}\right)^2 L_v$, where $\left(\frac{H}{W}\right)^2 L_v$ is the contribution of the excess portfolio variance to the variance of total wealth when an individual holds $H$ dollars in underdiversified equity and $W$ dollars in total assets. In dollars, this is equivalent to an annual dollar loss of $L_d = W L_r = \frac{\gamma}{2}\frac{H^2}{W} L_v$.

**CDF of Losses Due to Investing in Individual Stocks.** Figure F3 plots the CDF of losses faced by individuals in the SCF due to under-diversification, winsorizing the losses at the 95th percentile in each income group.

Figure F3: CDF of Losses Due to Investing in Individual Stocks




*Notes:* We plot the CDF of the annual losses due to under-diversification, winsorized at the 90th percentile.

**Confidence Intervals.** We construct confidence intervals for the under-diversification friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Evolution Over Time.** We use the 1998-2004, 2013-2019, and 2022 waves of the SCF to track the evolution of the friction over time, presenting the results in Table D1.

**Robustness Checks.** Tables Table F1 and Table F2 present two robustness checks for the under-diversification friction. Table F1 presents the point estimates if we define the friction as having ≥ 10% of wealth in ≤ 5 stocks, and Table F2 presents the point estimates if we define the friction as having ≥ 50% of wealth in ≤ 3 stocks.

Table F1: Investing in Individual Stocks Robustness Check: Proportion on Wealth Under-Diversified

| Income Group | $S_j$ Share with Positive non-Retirement Wealth | $F_j$ Share with ≥ 10% of Wealth in ≤ 5 Stocks | $L_j$ Average loss conditional on under-diversification | $S_j \cdot F_j \cdot L_j$ Expected Loss |
|---|---|---|---|---|
| Low Income | 0.281<br>(0.008) | 0.058<br>(0.008) | $349<br>[180, 844] | $6<br>[3, 13] |
| Middle Income | 0.451<br>(0.006) | 0.113<br>(0.006) | $529<br>[340, 726] | $27<br>[16, 36] |
| High Income | 0.686<br>(0.008) | 0.151<br>(0.007) | $1,163<br>[776, 1,604] | $120<br>[81, 167] |

*Notes:* We winsorize the losses at the 95th percentile, which is why the expected losses do not monotonically increase relative to Table 3.

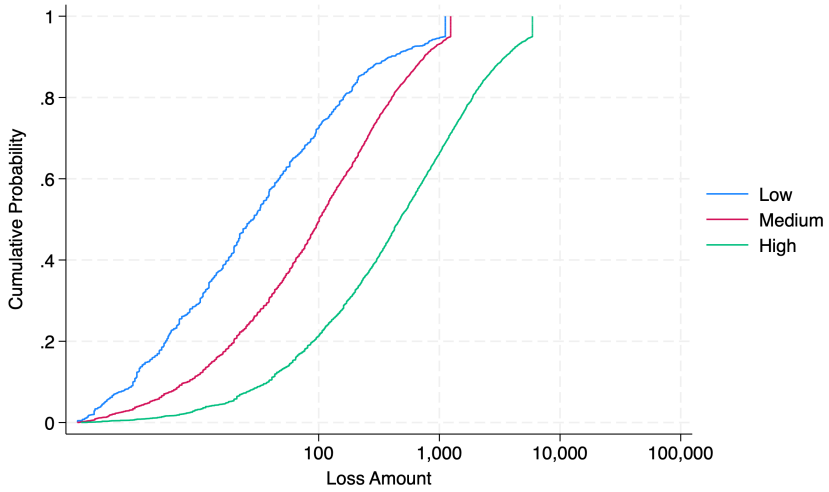
Table F2: Investing in Individual Stocks Robustness Check: Number of Stocks Under-Diversified

| Income Group | $S_j$ Share with Positive non-Retirement Wealth | $F_j$ Share with ≥ 50% of Wealth in ≤ 3 Stocks | $L_j$ Average loss conditional on under-diversification | $S_j \cdot F_j \cdot L_j$ Expected Loss |
|---|---|---|---|---|
| Low Income | 0.281 (0.008) | 0.024 (0.005) | $1,021 [557, 2,004] | $7 [3, 16] |
| Middle Income | 0.451 (0.006) | 0.041 (0.003) | $1,811 [1,274, 2,493] | $33 [21, 47] |
| High Income | 0.686 (0.008) | 0.047 (0.004) | $4,607 [2,533, 7,725] | $149 [80, 244] |

## F.5 Investing in High-Fee Mutual Funds

**CDF of Losses Due to Investing in High-Fee Mutual Funds.** Figure F4 plots the CDF of losses faced by individuals in the SCF due to excessive mutual fund fees, winsorizing the losses at the 90th percentile in each income group.

Figure F4: CDF of Losses Due to Investing in High-Fee Mutual Funds




*Notes:* We plot the CDF of the annual losses due to paying excessive mutual funds fees, winsorized at the 95th percentile.

**Confidence Intervals.** We construct confidence intervals for the excessive mutual fund fees friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. For the $F$ parameter, we draw a constant $F$ from the normal distribution $\mathcal{N}(0.91, 0.02906)$ in each bootstrap run. We have determined 0.02906 as the standard error of the $F$ estimate calculated from Choi et al. (2010) using the $\sqrt{\frac{p(1-p)}{N}}$ formula. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Evolution Over Time.** We use the 1998-2004, 2013-2019, and 2022 waves of the SCF to track the evolution of the friction over time, presenting the results in Table D1. While the wealth invested in mutual funds generally increased over time, the potential savings from looking for cheaper mutual funds decreased from 40 basis points to 39 basis points to 28 basis points, driving the overall evolution of $L_j$ and $S_j \cdot F_j \cdot L_j$ in opposite directions. In general, the former effect has dominated, resulting the potential savings from alleviating the friction increasing over time.

# Appendix G. Borrowing Frictions

## G.1 Not Refinancing a Mortgage

**Mortgage Rates Process.** We calibrate the following annual log interest rate process on 10-year nominal Treasury yields: $r_{t+1} = (1-\rho)\bar{r} + \rho r_t + \sigma\epsilon$, where $\epsilon \sim \mathcal{N}(0,1)$, and find the following parameters: $\rho \approx 0.9154, \bar{r} \approx 0.0558$, and $\sigma \approx 0.0111$. To convert from the annual log interest rate to the mortgage rate, we calculate $100(\tau e^{r_t} - 1)$, where $\tau \approx 1.0173$.

We calculate the average mortgage rates for each income group using the SCF from 2013-2019. We find that on average, high-income households have mortgage rates 55 basis points lower than middle-income households, and low-income households have mortgage rates 71 basis points higher than middle-income households. We calculate the same mortgage rate process for all households and then shift the mortgage rates of lower/higher income households by a constant amount. We winsorize the interest rates for high-income households at 173 basis points (equivalent to the 10-year treasure rate achieving the zero lower bound in our interest rate process), middle-income households at 228 basis points, and low-income households at 299 basis points.

**Mortgage Purchase Process.** We assign households to get a mortgage following the empirical proportions in Figure C1e, interpolated to cover every year of age. For example, for medium-income households we assume that 10.6% of households purchase a home at age 22 (as per the first green dot), 2.9% percent purchase at age 23, and so on. For households of age 50 and higher, we compute the share of households that purchase a new house by comparing the observed share with a mortgage in Figure 2 to the predicted share with a mortgage in the model simulation.

**Optimal Refinancing Threshold.** Using the Agarwal et al. (2013) notation, the optimal refinancing threshold is:

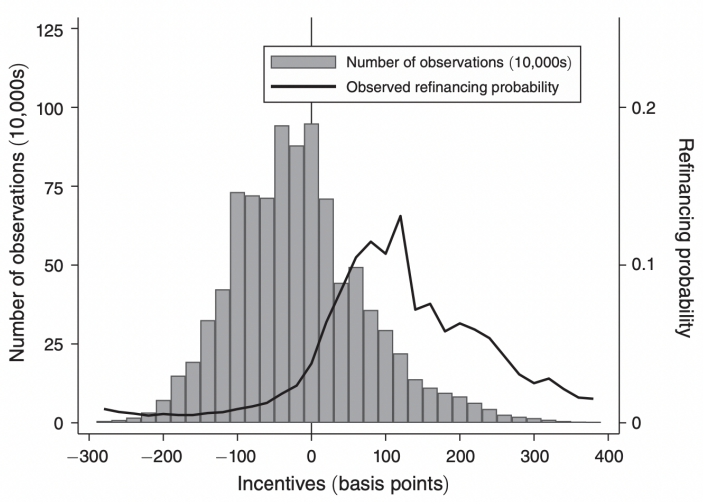
$$-\sqrt{\frac{\sigma\kappa}{M(1-\tau)}\sqrt{2(\rho+\lambda)}}, \tag{12}$$

where $\sigma$ is the standard deviation of the interest rate (estimated from historical mortgage interest rates); $M$ is the mortgage size; $\kappa$ is the transaction cost involved in refinancing the mortgage (equivalent to the inflation-adjusted Agarwal et al. (2013) cost: a fixed cost of \$2,500 and one interest rate point); $\tau$ is the marginal tax rate faced by the household; $\rho$ is the real discount rate (equal to the average nominal mortgage rate, minus the average inflation

rate from 1960–2024, plus one over the remaining life expectancy); and $\lambda$ is the expected repayment rate of the mortgage (equal to the probability of moving (assumed to be 0) + inflation (assumed to be 0) + the current interest rate $i$ divided by $e^{\Gamma i} - 1$, where $\Gamma$ is the number of years left in the mortgage).

**Refinancing Incentives.** We reproduce a key finding on household's incentives to refinance from Andersen et al. (2020). Figure G1 reproduces the key figure from Andersen et al. (2020), while Figure G2 shows how well we match it in our baseline simulations, and Figure G3 shows how well we match it with the model incorporating psychological costs. As you can see, we match the long right-tail of refinancing incentives, and our baseline simulation in Figure G2 roughly matches the observed average refinancing rate.

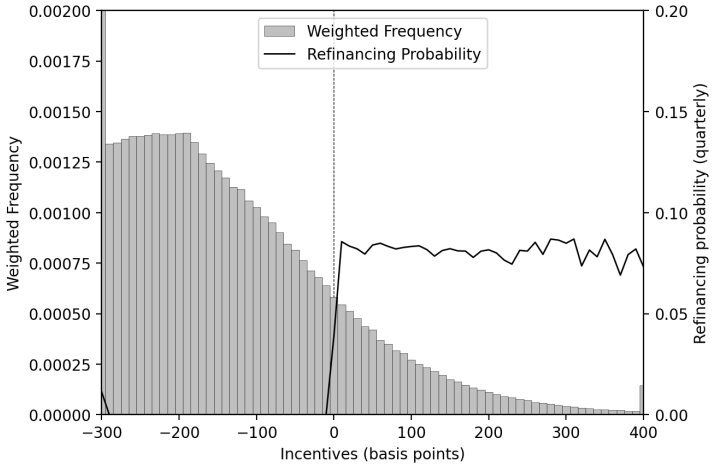
Figure G1: Refinancing Incentives




*Notes:* Reproduced from Andersen et al. (2020). The average mortgage in the plot above has 23 years left. The incentives on the x-axis are calculated after subtracting the optimal threshold for refinancing, so households should refinance at all incentives greater than 0.

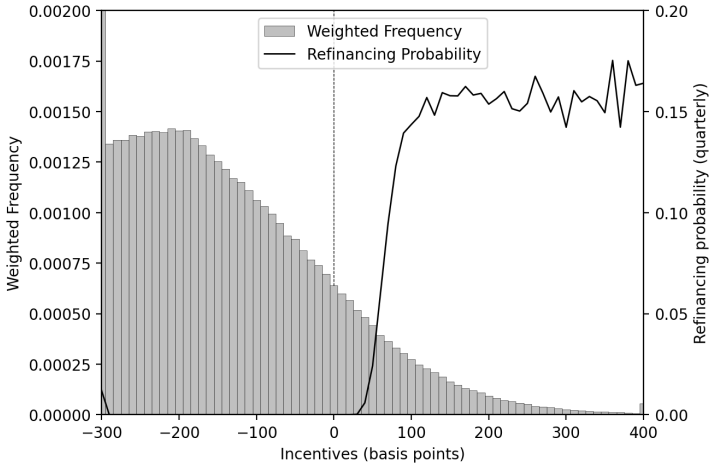
**Robustness: Psychological Costs.** This appendix presents robustness checks for our mortgage refinancing simulations, where we add in psychological costs similar to the Andersen et al. (2020) model. We add in psychological costs of refinancing on top of the Agarwal et al. (2013) minimum incentive to refinance, equal to 9,768 DKK for low-income households, 12,768 DKK for middle-income households, and 14,768 DKK for high-income households (converted to USD and inflated from 2010 to 2020 dollars). Matching the approach from Andersen et al. (2020), the model with the psychological costs has a lowered probability of being asleep. Table G1 presents our results by using this model.

Figure G2: Refinancing Incentives in Simulations




*Notes:* The average mortgage in the plot above has 19.27 years left. The incentives on the x-axis are calculated after subtracting the optimal threshold for refinancing, so households should refinance at all incentives greater than 0.

Figure G3: Refinancing Incentives in Simulations, with Psychological Costs




*Notes:* This robustness check includes psychological costs of refinancing, as determined from figure 9 of Andersen et al. (2020). The average mortgage in the plot above has 19.10 years left. The incentives on the x-axis are calculated after subtracting the optimal threshold for refinancing, so households should refinance at all incentives greater than 0.

Table G1: Mortgage Refinancing with Psychological Costs

| Income Group | $S_j$ Share with a Mortgage | $F_j$ Annual Probability of Not Checking for autorefinancing Opportunities | $L_j$ Average Loss Relative to Optimal Refinancing | $S_j \cdot F_j \cdot L_j$ Expected Loss |
|---|---|---|---|---|
| Low Income | 0.152 (0.012) | 0.604 (0.010) | $201 [nan, nan] | $31 [nan, nan] |
| Middle Income | 0.382 (0.008) | 0.502 (0.008) | $157 [90, 112] | $60 [34, 43] |
| High Income | 0.503 (0.010) | 0.479 (0.008) | $251 [140, 179] | $126 [70, 92] |

*Notes:* This robustness check includes psychological costs of refinancing, as determined from figure 9 of Andersen et al. (2020). $F_j$ is modeled as an i.i.d. friction across the years, as opposed to assuming that a fixed fraction of individuals have a persistent friction.

## G.2 Not Getting an Additional Mortgage Quote

**Computing Rejection Probabilities.** We estimate the share of mortgage applicants in each income group whose applications are rejected using the 2014 HMDA nationwide loan-application universe. We follow the action-code classification from Supplemental Appendix B.1 of Agarwal et al. (2024): applications with `action_taken` codes $\{1,6\}$ are classified as originated, codes $\{2,4,8\}$ as withdrawn or not taken, and codes $\{3,5,7\}$ as rejected. We compute the rejection probability as the share of all applications (originated, withdrawn, and rejected) that ended in rejection. We further restrict the sample to conventional, owner-occupied, first-lien applications for one-to-four-family non-manufactured dwellings for either home purchase or refinancing, and exclude applications with missing applicant income, which is required to construct income terciles. We define income groups as terciles of `applicant_income_000s` computed within the 2014 sample. The resulting rejection probabilities by income group are reported in Table G2.

Table G2: Mortgage Application Rejection Probabilities by Income Group

| Income Group | Pr(Rejected) |
|---|---|
| Low | 0.300 |
| Middle | 0.203 |
| High | 0.169 |

*Notes:* Mortgage application rejection probabilities by income group, computed from the 2014 HMDA nationwide loan-application universe. The number of applications is 1,810,766 (Low), 1,752,879 (Middle), 1,779,455 (High), for a total of 5,343,100.

**Calculating Dollar Losses.** To calculate $L$ and $SFL$, we implement simulations of household purchasing and refinancing using our model data, similar to those implemented for the mortgage refinancing frictions (subsubsection 2.3.1). Individuals purchase houses following the observed rates of home ownership in the SCF, and they refinance whenever it is optimal for them to do so (per the Agarwal et al. (2013) threshold) and they are 'awake', actively checking for refinancing opportunities. We assume that a share of individuals is rejected whenever they

seek an additional mortgage quote (per Table G2), giving us four groups of individuals: individuals affected by the friction who would be approved for the additional mortgage quote, individuals not affected by the friction who would be approved for the additional quote, individuals affected by the friction who would not be approved for the additional quote, and individuals not affected by the friction who would not be approved by the additional quote.

In the baseline, friction on, scenario, only individuals who are not affected by the friction and will be approved for an additional mortgage quote enjoy an overall lower path of mortgage interest rates. When we turn the friction off, the group that was formerly affected by the friction will be receive a lower path of mortgage interest rates. The group that would not be approved for the additional mortgage quote never enjoys the lower interest rate. The reduction in the mean interest rate equals the mean basis point loss (conditional on being above 10 basis points) per Bhutta et al. (2026) and is approximately 30 basis for all income groups. Using our determined interest rate paths, we simulate household mortgage payments and refinancing opportunities, computing the total lifetime savings of affected, approved households if they had gotten an additional quote on their mortgage. We divide their lifetime savings by the number of years their mortgage is active in the baseline scenario to determine $L$, and we similarly average across their potential savings to determine $SFL$.

## G.3 Suboptimally Repaying Credit Card Debt

**Mean Credit Card Borrowing in UK.** For individuals borrowing on 2 credit cards, the mean annual saving (in British pounds) is 65 pounds (Table 2 of Gathergood et al. (2019), Panel B), which is 1.5 percent of the average revolving credit card balance over the two cards, equal to 4,250 pounds (Table 1, summing over the average balance for the high-APR card and the low-APR card). We can similarly compute the average saving for individuals with 3 credit cards as 121/6,300, that is, 1.9 percent. We thus compute that individuals borrowing on 2+ credit cards could save annually 1.7 percent of their annual credit card balance. We then apply this percent saving to the average credit card balance by age-income profile to compute the annual loss $L_j$ due to suboptimal credit card repayment.

**Confidence Intervals.** We construct confidence intervals for the suboptimal repayment friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. In each bootstrap run, we draw a constant $F$ parameter from the normal distribution $\mathcal{N}(0.88, 0.00056)$ and a constant annual potential savings rate from the normal distribution $\mathcal{N}(0.017, 0.00005)$. We have estimated 0.00056 as the standard error of the $F$ estimate from Gathergood et al. (2019) using the delta method, assuming 0.85 is a fixed theoretical benchmark (with no variance and no correlation with the proportion of people actually repaying debt optimally) and calculating the variance of 0.1 using the $\frac{p(1-p)}{N}$ formula.[2] We estimate the standard error of the savings rate as 0.00005 by calculating the weighted mean of the variances in savings rate among people with 2+ credit cards. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially

[2] When calculating the variances of estimates from people with $n$ cards, we divide by the number of account-months in the dataset, rather than by the number of unique individuals. While this understates the standard error, we do not have information on the precise number of unique individuals.

asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Evolution Over Time.** We use the 1998-2004, 2013-2019, and 2022 waves of the SCF to track the evolution of the friction over time, presenting the evolution of $S_j$, $L_j$, $S_j \cdot F_j \cdot L_j$ over time in Table D1. Lacking additional information, we assume the information from Gathergood et al. (2019) on the proportional of people suboptimally repaying their debt and their potential savings is constant over time.

## G.4 Paying Late Fees

**Comparing with Administrative Data.** We estimate the share with a credit card $S_j$ as well as the share $F_j$ of cardholders paying a late fee in the last 12 months using the publicly-available survey data from the 2023, 2024, and 2025 Making Ends Meet survey from the CFPB (2024b). This dataset only has categorical variables for income and age rather than exact estimates. This means that our measures of income groups don't always follow a perfect 25-50-25 low/middle/high income split, but we try to approximate the 25-50-25 splits as much as possible. Given that survey responses may not correctly report the extent of credit card usage or borrowing, we scale these estimates using administrative data from CFPB (2021, 2023, 2024a). CFPB (2021) estimates that 70.2% of US individuals owned credit cards in 2020. Since the corresponding $S_j$ estimate in the survey data is 80.7%, we scale down our estimate of $S_j$ to match the administrative data. Additionally, CFPB (2024a) and CFPB (2023) estimate that 23.68% of cardholders paid any late fees in 2022. Our overall estimate for $F_j$ in the survey data is 23.26%, which is reasonably close to the administrative data estimate.

**Confidence Intervals.** We construct confidence intervals for the late fees friction by bootstrapping 7,468 individuals from the CFPB 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

## G.5 Paying Overdraft Fees

The annual loss $L_j$ is the average overdraft fee, \$35, times the number of overdrafts. As per our CFPB survey data, conditional on overdrafting at least once, the average person overdrafts 5.793 times in a year. The number of overdrafts is a categorical variable in the CFPB survey data. To calculate the mean we impute individuals with 1-3 overdrafts as having 2 overdrafts, individuals with 4-10 overdrafts as having 7 overdrafts, and individuals with 10+ overdrafts as having 25 overdrafts. In the administrative data from Low et al. (2017), the corresponding number of average overdrafts is 8.480. The number of overdrafts is represented categorically in the admin data as well. To calculate the mean, we impute individuals with 1-3 overdrafts as having 2 overdrafts, individuals with 4-10 overdrafts as having 7 overdrafts, individuals with 11-20 overdrafts as having 15 overdrafts, and individuals with 20+ overdrafts as having 25 overdrafts. We thus scale up the number of overdrafts in the survey data (and thus our estimates for $L_j$) by 8.480/5.793.

**Confidence Intervals.** We construct confidence intervals for the overdraft fees friction by bootstrapping 7,468 individuals from the CFPB 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

# Appendix H. Insurance Frictions

## H.1 Choosing Dominated Health Insurance

**Confidence Intervals.** We construct confidence intervals for the dominated insurance friction by bootstrapping 16,499 individuals from the SCF 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. In each bootstrap run, we draw a constant number from the normal distribution $\mathcal{N}(0.37, 0.02654)$ to multiply by the proportion of people with employer-provided insurance, to determine $S$. We determine 0.02654 as the standard error for the proportion of companies with dominated insurance plans using the $\frac{p(1-p)}{N}$ formula, with $N = 331$ from Liu and Sydnor (2022). We also draw a constant number from the distribution $\mathcal{N}(0.62, 0.00628)$ to determine the $F$ for low-income people, a constant number from the distribution $\mathcal{N}(0.52, 0.00457)$ to determine the $F$ for mid-income people, and a constant number from the distribution $\mathcal{N}(0.40, 0.00634)$ to determine the $F$ for high-income people. We calculate all these standard errors using the $\frac{p(1-p)}{N}$ formula, with $N = 23,881$ (from Bhargava et al. (2017)). We additionally draw a constant $L$ from the normal distribution $\mathcal{N}(1121, 5.97521)$. We know 723 is the standard error for the loss directly from Liu and Sydnor (2022), which we divide by the number of firms who offer a dominated insurance choice (121) to obtain the standard error 5.97521. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

## H.2 Suboptimally Lapsing Life Insurance

**Estimating Life Insurance Prevalence and Policy Size.** Figure C1j plots, for each income group and age bin, the share of individuals with a long-duration TLI, as well as a representative policy face value. The age bins are rounded down, so, for example, the proportion of people with TLI at 25 is equivalent to the average proportion of people who own TLI between 25 and 30, and similarly for later age groups. For each age bin, we take the share with a reported TLI and deflate it by 0.73, as we estimate that 73% of TLI are for durations of 15 years or longer.[3]

We additionally compute the representative policy face value for an age-income group as the midpoint between the 25th and 75th percentile policy face values. We use the midpoint as a measure of policy size because the mean is easily distorted by large outliers, and the median understates the policy size. The SCF unfortunately does not include the duration of the TLI, so we do not differentiate between short-duration vs long-duration TLIs when

[3] Friedrich and Saip (2022) show that, in 2020, 26.3% of TLI policies were for 1, 5, or 10-years, 51.9% of policies are for 15 or 20-years, 17.4% of policies are for 25 or 30-years, and 4.5% of policies have other durations. We make the simplifying assumption that 73.7% of all TLI policies are 20-year policies that could benefit from switching to a 10-year plan if early lapsing occurs.

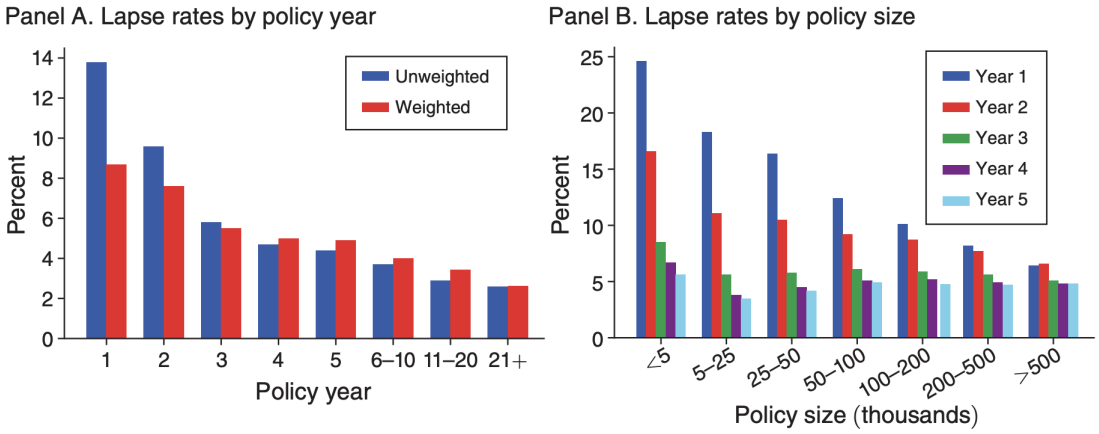
determining the policy face value.

**Imputing TLI Purchases.** Figure H2 illustrates how we use the cross-sectional holdings of TLI and the Figure H1 lapsing rate to back out the rate of new purchases of TLI. For example, starting from the cohort at age 25, we apply the rate of lapsing to the age-25 cohort, with the red dots indicating the residual members of that cohort with an active TLI. For the first 5 years after purchase, we use Figure H1B to determine the rate of lapsing, using the average policy size in an income-age group to determine the relevant lapsing rate. For years 6-10, we instead impute the constant lapsing rate of ~4% from Figure H1A. We then estimate the share of people purchasing a new life insurance policy at age 30 as the difference between the share of people cross-sectionally holding a long-duration TLI at age 30 in the SCF (the brown dot) and the imputed number of individuals still holding the TLI purchased at age 25 (the green dot). The difference gives the blue dot at age 30, which is the imputed share of individuals purchasing a new TLI at age 30. We apply a similar procedure for each 5 year group. The implied blue dots produce a reasonable pattern of new TLI purchases, with new purchases declining later in life. We note that any estimate of the share of people with a friction depends on an assumption over the autocorrelation, that is, whether individuals who display the friction at one time will also display it in the future. We assume perfect auto-correlation, that is, an individual who lapses in a 5-year age period would also lapse again if they were to repurchase a TLI.

Using Compulife (2013) data on both the 10-year and 20-year TLI premiums across several insurance providers, we estimate that the 10-year policy is 15-25 log points cheaper than a corresponding 2-year policy, with a larger difference at older ages (since the mortality increase becomes steeper) (as illustrated in Figure H3). We assume individuals have regular health, are non-smokers, and purchased a 20-year TLI in California, October 2019. We use the medians (i.e., black dots) to determine the annual saving from switching for each income-age group.

We estimate the average annual savings available to early lapsers across all years in which they overpay for their policy. For example, for low income individuals who purchase a long-duration TLI policy at age 25, the potential annual savings per year (from switching to a 10-year policy) is $23. For the 2.0% of the total (low-income) population that lapses in the first year (equal to the vertical gap between the brown and first red dot in Figure H2a), we impute an average yearly loss of $23/5 (since they lose $23 in year 1 and 0 in the next years). Similarly, 1.3% lapse in the second year with a loss of $23*2/5, 0.8% lapse in the third year with a loss of $23*3/5, 0.6% lapse in the fourth year with a loss of $23*4/5, and 0.5% lapse in the fifth year with a loss of $23*5/5. Averaging across these groups, the average yearly saving (among those who lapse) is $10.75, as displayed in Table H1. We distribute the savings evenly annually among the 5.1% of low-income individuals who lapse.

Figure H1: Lapsing Rate by Policy Size



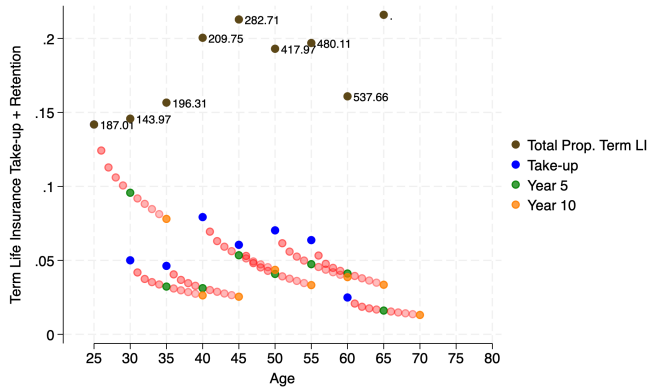

*Notes:* Reproduced from Gottlieb and Smetters (2021), Figure 1.

Table H1: Life Insurance Lapsing Parameters by Age and Income Group

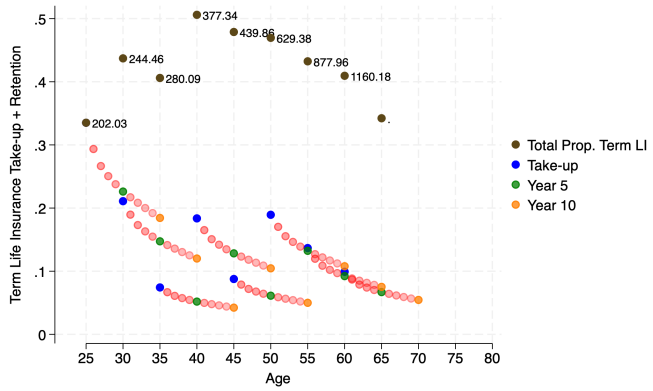
| Income Group | Age | $S_j$ | $F_j$ | $L_j$ |
|---|---|---|---|---|
| Low | 25 | 0.1575 | 0.3252 | 10.75 |
| Low | 30 | 0.1683 | 0.2472 | 20.53 |
| Low | 35 | 0.1775 | 0.1347 | 19.59 |
| Low | 40 | 0.2062 | 0.1389 | 31.43 |
| Low | 45 | 0.2141 | 0.1320 | 42.59 |
| Low | 50 | 0.2173 | 0.1789 | 65.92 |
| Low | 55 | 0.1859 | 0.1434 | 124.79 |
| Low | 60 | 0.1773 | 0.1226 | 111.07 |
| Middle | 25 | 0.3302 | 0.3252 | 15.22 |
| Middle | 30 | 0.4297 | 0.2409 | 35.10 |
| Middle | 35 | 0.4043 | 0.1242 | 57.10 |
| Middle | 40 | 0.5042 | 0.1298 | 62.19 |
| Middle | 45 | 0.4761 | 0.1045 | 117.46 |
| Middle | 50 | 0.4614 | 0.1429 | 123.83 |
| Middle | 55 | 0.4383 | 0.1627 | 212.03 |
| Middle | 60 | 0.4033 | 0.1187 | 325.43 |
| High | 25 | 0.4407 | 0.3015 | 22.80 |
| High | 30 | 0.4997 | 0.2295 | 52.91 |
| High | 35 | 0.5578 | 0.1293 | 83.57 |
| High | 40 | 0.5918 | 0.1098 | 158.54 |
| High | 45 | 0.5907 | 0.0912 | 251.43 |
| High | 50 | 0.5691 | 0.1417 | 313.53 |
| High | 55 | 0.5451 | 0.1388 | 587.92 |
| High | 60 | 0.4921 | 0.1094 | 926.66 |

*Notes:* $S_j$ is the share of individuals with a long-duration term life insurance policy. $F_j$ is the share of policy holders who lapse within the first 10 years. $L_j$ is the average annual dollar saving from switching to a 10-year policy. Parameters are reported separately by 5-year age bucket and permanent income group.

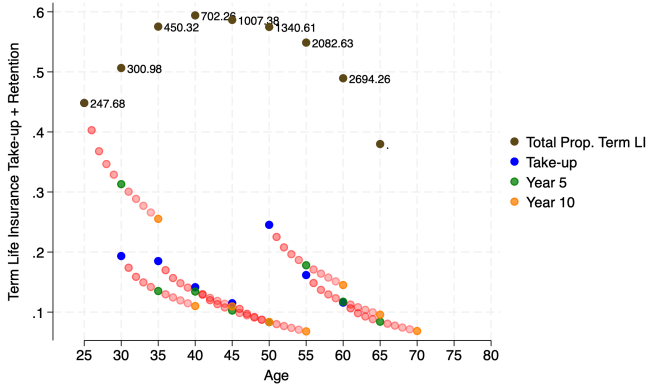
Figure H2: TLI Purchase and Lapsing by Income Group




(a) Low Income



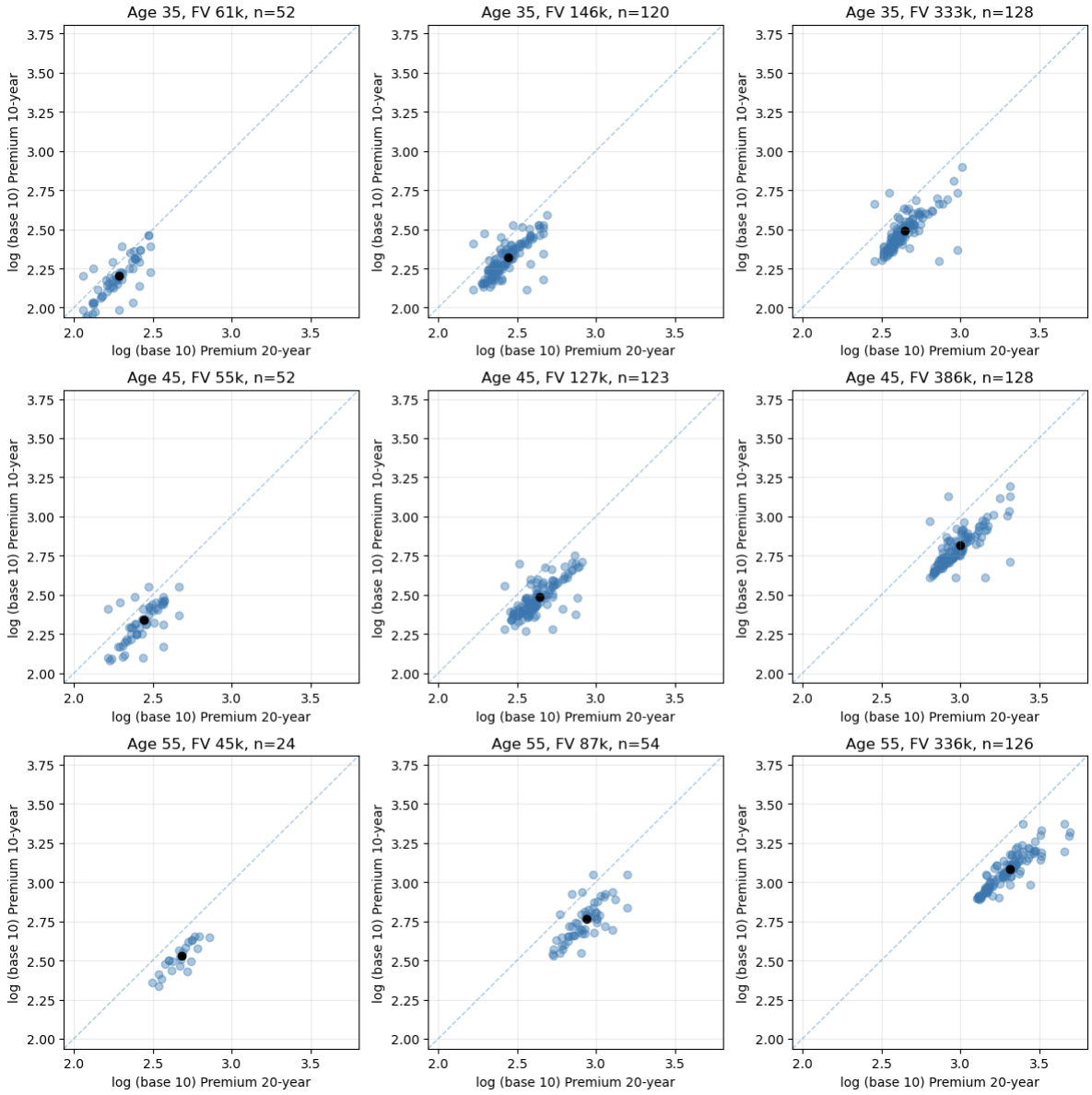

(b) Middle Income




(c) High Income

*Notes:* We plot the rate of long-duration TLI purchase and retention for low-, middle-, and high-income individuals. Brown dots indicate cross-sectional ownership of life insurance from the SCF, with numbers near the dots indicating the mean 20-year policy premium associated with the policy size at the midpoint of the 25th and 75th percentiles of all policy sizes in that age group. Red dots illustrate the rate of TLI policy retention after each year under lapsing calculations based on Gottlieb and Smetters (2021). The proportions of individuals retaining their policies up to years 5, 10, 15, and 20 are marked in distinct colors. Blue dots indicate the proportion of individuals who purchase TLI at the start of each interval, calculated to match the cross-sectional ownership rates shown by the brown dots.

Figure H3: Sample 10-Year vs 20-Year TLI Premiums Across All Providers and Income Groups




*Notes:* We plot 10-year vs 20-year TLI premiums across various ages and policy sizes. The blue dots represent a company with both 10-year and 20-year TLIs, and the black dots illustrate the mean 10-year and 20-year policy premiums across companies.

# Appendix I. Benefits Frictions

## I.1 Not Claiming EITC Benefits

**2020 EITC Schedule.** Figure I1 plots the 2020 EITC schedule, depending on a households tax filing status and number of children.

Figure I1: 2020 EITC Cutoffs

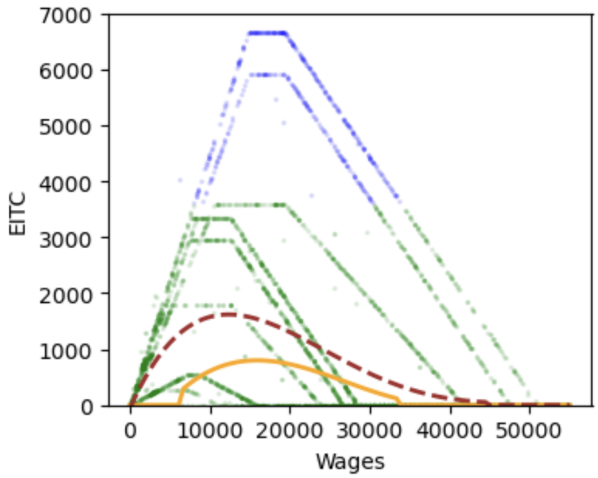



*Notes:* We plot the 2020 EITC schedules, separately for each household tax filing status and number of children.

**Confidence Intervals.** We construct confidence intervals for the not claiming EITC friction by bootstrapping 14,197 individuals from the PSID 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. For the $F$ parameter, we draw a constant $F$ from the normal distribution $\mathcal{N}(0.2, 0.00009)$ in each bootstrap run. We have determined 0.00009 as the standard error of the $F$ estimate calculated from Coleman et al. (2024) using the $\sqrt{\frac{p(1-p)}{N}}$ formula. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Model Implementation.** We model perfect EITC claiming by households eligible for more than $3,584, and an overall claiming rate of 78.8% among all other households. We have calibrated the above parameters to match an overall EITC individual participation rate of 80% and an overall dollar participation rate of 85%, per Coleman et al. (2024), using the PSID from 2011-2019. We also average the amount of EITC available across households with varying number of kids, as illustrated in Figure I2.

Figure I2: PSID EITC for Ages 30–34




*Notes:* We plot the amount of EITC available versus the individual wages using data from individuals aged 30-34 in the 2011-2019 PSID. The scatter points represent the amount of EITC an individual from the PSID was eligible for (after dividing EITC amounts evenly among married couples), with the blue points lying above the perfect claiming threshold ($3,584) and the green points lying below. The dashed red line is a quartic regression fit on all the points, representing the amount of EITC someone is eligible for if they always claim EITC. The solid orange line is a spline regression fit on just the blue points, substituting the green points for zeros, and represents the amount of EITC individuals are always eligible for, even if they don't claim below the threshold.

Figure I2 illustrates how we model the amount of EITC available to those who always claim EITC and to those who only claim above the threshold. The dashed red line represents the amount of EITC available to the 78.8% of the modelled population that always claims EITC, and the orange line represents the amount of EITC available to the 21.2% of the population who only claim above the threshold. Since households vary in the number of kids, and thus subsequently the amount of EITC available, over the lifecycle, we model separate fits for each 5-year age bin in our model. Figure I2 illustrates the fit for individuals between 30 and 34 years old.

Table I1: Model Implementation on the 2011-2019 PSID

| | Proportion Eligible ($S$) | Proportion Not Claiming ($F$) | Loss due to Not Claiming ($L$) | Expected Loss ($S * F * L$) |
|---|---|---|---|---|
| Low Income | 0.634 | 0.212 | $482 | $65 |
| Middle Income | 0.325 | 0.212 | $313 | $22 |
| High Income | 0.036 | 0.212 | $218 | $2 |

Table I1 reconstructs Table 3 using our model implementation on the 2011-2019 PSID. Since our modeling approach involves averaging across married and unmarried households with and without kids, the proportion eligible ($S_j$) is significantly overstated in our model. To counteract that, the loss $L_j$ is sizably lower in our model. The overall expected loss ($S_j * F_j * L_j$) in the model matches reasonably well the observed EITC data, about 20 percent larger for the low- and middle-income groups (and overstated for the high-income group, though still very low).

## I.2 Not Claiming SNAP Benefits

**SNAP Schedule.** Table I2 showcases the FY 2020 SNAP cutoffs. We apply the standard deduction, earned income deduction, shelter deduction, and healthcare and childcare deductions when computing the net income. We ignore the homeless shelter deduction since the PSID does not include homeless households in their sampling strategy. If a household is eligible for SNAP, the total available amount can be calculated as the maximum allotment minus 30% of net income, with the lowest possible amount available being the minimum allotment for the state (which varies by state, but equals $16 monthly for the 48 contiguous states and DC).

Table I2: Monthly SNAP Eligibility Cutoffs and Allotments for 48 States and D.C. (FY 2020)

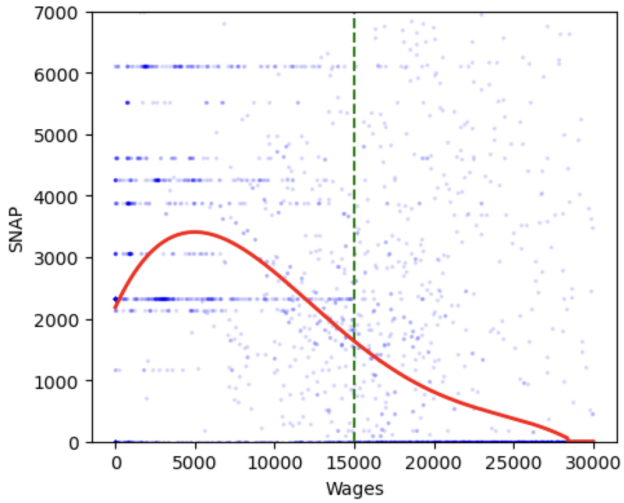
| HH Size | Gross Income Cutoffs | Net Income Cutoffs | Standard Deduction | Max. Allotment |
|---|---|---|---|---|
| 1 | $1,354 | $1,041 | $167 | $194 |
| 2 | $1,832 | $1,410 | $167 | $355 |
| 3 | $2,311 | $1,778 | $167 | $509 |
| 4 | $2,790 | $2,146 | $178 | $646 |
| 5 | $3,269 | $2,515 | $209 | $768 |
| 6 | $3,748 | $2,883 | $240 | $921 |
| 7 | $4,227 | $3,251 | $240 | $1,018 |
| 8 | $4,705 | $3,620 | $240 | $1,164 |
| Each add'l member | +$479 | +$369 | +$0 | +$146 |

*Notes:* FY 2020 SNAP cutoffs for the contiguous 48 states, DC, Guam, and the Virgin Islands. Households in Hawaii and Alaska have different eligibility cutoffs and allotments, which we account for but do not report here. Elderly and disabled households do not need to meet the gross income cutoffs, only the net income cutoffs.

**Confidence Intervals.** We construct confidence intervals for the not claiming SNAP friction by bootstrapping 14,197 individuals from the PSID 300 times. In each bootstrap run, we re-calculate and store the $S, F, L, S \cdot F \cdot L$ parameters for each of the three income groups. For the $F$ parameter, we draw a constant $F$ from the normal distribution $\mathcal{N}(0.18, 0.00005)$ in each bootstrap run. We have determined 0.00005 as the standard error of the $F$ estimate calculated from Vigil (2022) using the $\sqrt{\frac{p(1-p)}{N}}$ formula. We present the results of the bootstrap in Table 3, providing standard errors for the symmetric $S$ and $F$ estimates and confidence intervals for the potentially asymmetric $L$ and $S \cdot F \cdot L$ estimates.

**Model Implementation.** Per table 2 in Vigil (2022), we model perfect SNAP claiming among households under the federal poverty limit (FPL), and a claiming rate of 42% among households above the FPL. Figure I3 illustrates our modelling approach.

Figure I3: PSID SNAP for Ages 30–34




*Notes:* We plot the amount of SNAP available versus the individual wages using data from individuals aged 30-34 in the 2011-2019 PSID. The solid red line is fit on all the scatter points, and the dashed green line represents the average FPL for 30-34 year old individuals (since the FPL scales based on number of children).

As illustrated in Figure I3, we model perfect SNAP claiming (i.e., following the red line completely) among the 42% of the individuals that are not affected by the friction. For the 58% of the individuals that are affected by the friction, we model perfect claiming when income is below the average FPL (represented by the dashed green line) and 0 claiming when income is above that. Since household sizes varies across the lifecycle, and SNAP and the FPL both scale with household size, we calculate separate SNAP eligibility fits (i.e., the red line) and average FPLs (i.e., the dashed green line) in each 5-year age bins. Figure I3 represents the fit for 30-34 year old individuals.

Table I3: Model Implementation on the 2011-2019 PSID

| | Proportion Eligible ($S$) | Proportion Not Claiming ($F$) | Loss due to Not Claiming ($L$) | Expected Loss ($S*F*L$) |
|---|---|---|---|---|
| Low Income | 0.880 | 0.580 | \$752 | \$399 |
| Middle Income | 0.423 | 0.580 | \$465 | \$124 |
| High Income | 0.121 | 0.580 | \$400 | \$26 |

Table I3 reconstructs Table 3 using our model implementation on the 2011-2019 PSID. Since our modeling approach involves averaging across married and unmarried households with and without kids, the proportion eligible ($S_j$) is higher in our model. Counteracting that, the average loss due to not claiming ($L_j$) is lower. Overall, we match the expected loss ($S_j * F_j * L_j$) quite well.

# Appendix J. Health Frictions

## J.1 Not Taking Statin Medications

**Mortality Impact.** Table J1 summarizes the result of several medical RCTs documenting the impact of Statin Medications.

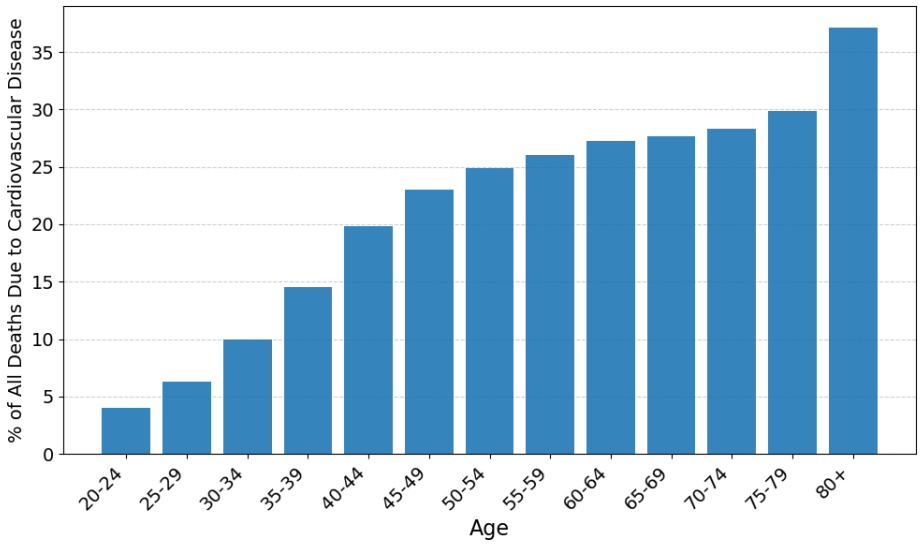
Table J1: Impact of Statins on Cardiovascular Outcomes: RCT Evidence

| Paper (Data Source) | ITT on Cardiovascular Episode | TOT on Cardiovascular Episode | ITT on Cardiovascular Mortality | TOT on Cardiovascular Mortality |
|---|---|---|---|---|
| Sever et al. (2003) (ASCOT-LLA) | -36% (-50%, -17%) | -46% | -10% (-34%, +23%) | -13% |
| Heart Protection Study Collaborative Group (2002) (HPS) | -24% (-28%, -19%) | -35% | -17% (-25%, -9%) | -25% |
| Downs et al. (1998) (AFCAPS/TexCAPS) | -37% (-50%, -21%) | -37% | -23% ( , ) | -23% |
| Shepherd et al. (1995) (WOSCOPS) | -31% (-43%, -17%) | -31% | -28% (-52%, +10%) | -28% |
| Ridker et al. (2008) (JUPITER) | -44% (-54%, -31%) | -59% | -20% (-33%, -3%) | -27% |
| Sacks (1996) (CARE) | -25% (-39%, -8%) | -25% | -20% (-39%, +5%) | -20% |
| Scandinavian Simvastatin Survival Study Group (1994) (4S) | -30% ( , ) | -30% | -35% (-48%, -20%) | -35% |
| The LIPID Study Group (1998) (LIPID) | -29% (-38%, -18%) | -29% | -25% (-35%, -13%) | -25% |
| **Precision-Weighted Average** | **-28.1%** (1.8%) | **-35.2%** (2.2%) | **-21.8%** (2.6%) | **-26.5%** (3.1%) |

*Notes:* The studies AFCAPS/TexCAPS, WOSCOPS, CARE, and 4S do not report a first stage of compliance (or use ITT as TOT). For JUPITER, we use the estimate for overall mortality, as the impact on cardiovascular mortality is not reported. Averages are equal-weighted across all studies.

For context, Figure J1 depicts the percent of all deaths due to Cardiovascular Disease between 2011 to 2019. In the model, we instead use the 56.9 percent share of deaths due to cardiovascular disease from subsubsection 2.6.1 to determine the statin mortality multiplier, as detailed in subsection K.4.

Figure J1: Percent of All Deaths Due to Cardiovascular Disease (2011–2019)




*Notes:* We plot the proportion of all deaths that occurred due to cardiovascular diseases from 2011-2019. We obtain data from the National Center for Health Statistics (2021), following the default classification of cardiovascular disease deaths as the deaths with ICD-10 codes of I00-I78.

**Financial Costs.** In the no-friction scenarion, we assume that everyone takes the statin medications that are appropriate, which typically costs around $8 per month, or $96.48 annually for the uninsured (Drugs.com, 2026). We use the NHIS to calculate that 27% of low-income people, 12% of middle-income people, and 3% of high-income people are uninsured.

**Decomposition.** Table J2 decomposes the $L$ and $S \cdot F \cdot L$ of the statins friction into its monetary (i.e., insurance costs) and health components.

Table J2: Decomposition of $L, SFL$ for the Not Taking Statin Medications Friction

| Income group | $S$ | $F$ | $L$ | | | $S \cdot F \cdot L$ | | |
|---|---|---|---|---|---|---|---|---|
| | | | Health | Monetary | Total | Health | Monetary | Total |
| Low | 0.443 | 0.469 | $594 | $26 | $620 | $123 | $5 | $129 |
| Middle | 0.449 | 0.404 | $1,020 | $11 | $1,032 | $185 | $2 | $187 |
| High | 0.478 | 0.357 | $1,066 | $3 | $1,069 | $182 | $1 | $183 |

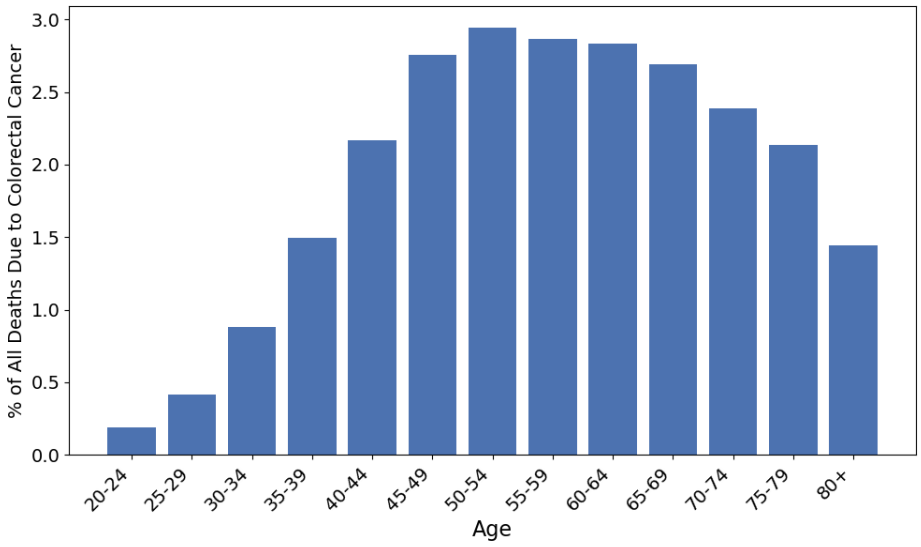
**Confidence Intervals.** To construct confidence intervals for the statins friction, we perform 300 bootstrap draws for $S$ (using the NHIS), $F$ (using the confidence intervals provided in Verma et al. (2017)), and $L$. To perform the bootstrap draws for $L$, we draw the increased mortality risk due to not taking statins from a normal distribution with mean 26.5% and SD 3.1%, per Table J1. Across all $L$ bootstrap draws, we assume that i) the baseline mortality risk (i.e., the mortality risk you face if you are not affected by the friction) is constant, and is calibrated using the

procedure described in subsection K.4, ii) the average financial loss per additional death is constant at each age, and iii) the only thing that varies is the increased mortality risk, which is used to calculate the increase in the proportion of deaths that occur at each age. In other words, we determine both the baseline mortality and the average financial loss per additional death at each age using our lifecycle model with increased statins mortality 26.5%, vary the proportion of additional deaths at each age based on the drawn increased mortality risk, and calculate the total $L$ for each bootstrap by multiplying the proportion of additional deaths times the average financial loss per additional death. To determine our bootstrap for $S * F * L$, we simply multiply all 300 draws of our bootstraps for $S$, $F$, and $L$.

## J.2 Not Screening for Colon Cancer

**Mortality Impact.** Figure J2 depicts the percent of all deaths due to Colorectal Cancer between 2011 to 2019, which is relevant for translating CRC-specific mortality effects into all-cause mortality effects.

Figure J2: Percent of All Deaths Due to Colorectal Cancer from 2011–2019




*Notes:* We plot the percent of all deaths due to colorectal cancer by age group from 2012-2020, using data from the Centers for Disease Control and Prevention (2021).

**Financial Costs.** In the no-friction scenarion, we assume that everyone does annual fecal testing similar to Mandel et al. (1993), which a 6.3% chance of testing positive (per Miuţescu et al. (2013)), in which case they ought to do a sigmoidoscopy similar to Shroff et al. (2014). For the uninsured, the fecal testing costs $24 and the sigmoidoscopy costs $360 on average (Gastroenterology Medical Clinic, 2026), for a total expected annual cost of around $47. We use the NHIS to calculate that 27% of low-income people, 12% of middle-income people, and 3% of high-income people are uninsured.

**Decomposition.** Table J3 decomposes the $L$ and $S \cdot F \cdot L$ of the colonoscopy friction into its monetary (i.e., insurance costs) and health components.

Table J3: Decomposition of $L, SFL$ for the Colonscopy Friction

| Income group | $S$ | $F$ | $L$ | | | $S \cdot F \cdot L$ | | |
|---|---|---|---|---|---|---|---|---|
| | | | Health | Monetary | Total | Health | Monetary | Total |
| Low | 0.465 | 0.619 | \$29 | \$12 | \$40 | \$8 | \$3 | \$12 |
| Middle | 0.466 | 0.524 | \$37 | \$6 | \$43 | \$9 | \$1 | \$11 |
| High | 0.461 | 0.439 | \$43 | \$2 | \$45 | \$9 | \$0 | \$9 |

## J.3 Failing to Quit Smoking

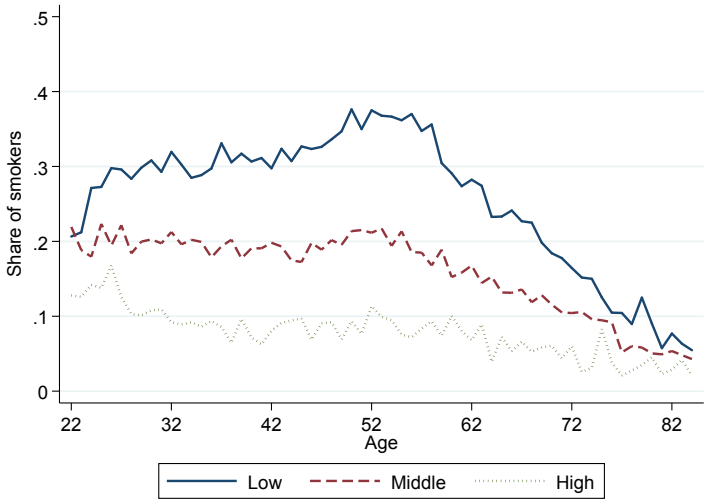
**Mortality Impact.** The mortality factors in Table J4 are estimated separately by income group. The sample-share-weighted averages of these income-group-specific factors are 2.37 and 1.90 for ages 50–74 and 75+, respectively, while the corresponding factors estimated from the sample pooled across income groups are 2.92 and 1.90. The larger pooled estimate for ages 50–74 reflects compositional effects, whereby low-income individuals are concentrated in the late-quitting group. The mortality impact of smoking amounts to a shorter life expectancy at 50 by 6.7 years. This estimated reduction understates the impact on life expectancy due to our data limitations, which require us to effectively assume that everyone dies with certainty at the age of 89. Under a conservative assumption that everyone alive at the end of the sample lives for an additional 5 years, the life expectancy gap increases to 8.0 years.

Table J4: Failing to Quit Smoking Friction Losses Summary

| Income Group | $S$<br>Share Wanting to Quit by 50 | $F$<br>Share Failing to Quit by 50 | $L_{50\text{-}74}, L_{75+}$<br>Increased mortality factor (50-74, 75+) | $L_{\text{Income}}$<br>Expected financial loss |
|---|---|---|---|---|
| Low Income | 0.414 | 0.562 | 2.24, 1.97 | – |
| Middle Income | 0.350 | 0.414 | 2.57, 1.80 | – |
| High Income | 0.299 | 0.241 | 2.07, 2.08 | – |

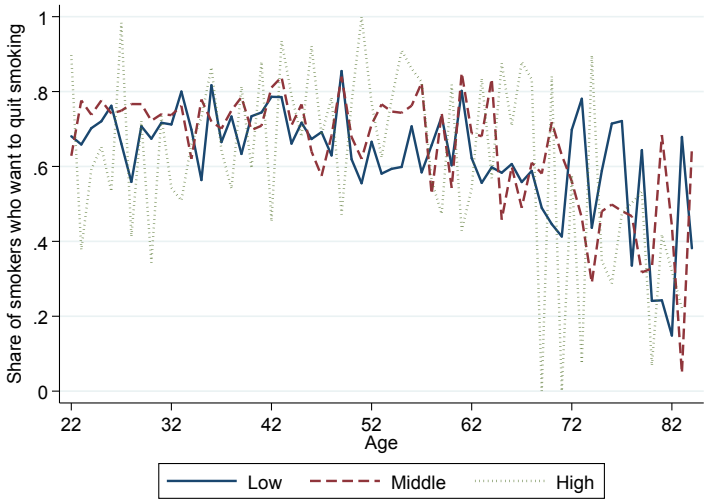
Figure J3 uses the NHIS to plot the share of current smokers by age and income group, while Figure J4 plots the share of current smokers who want to quit smoking by age and income group. Figure J5 and Figure J6 both plot the mortality of former and never smokers relative to current smokers, but Figure J5 restricts to our main sample, which is ages 50+. The figure shows that smokers who quit by age 50 forego a lot of the mortality impacts.

Figure J3: Share of Smokers by Age and Income Group



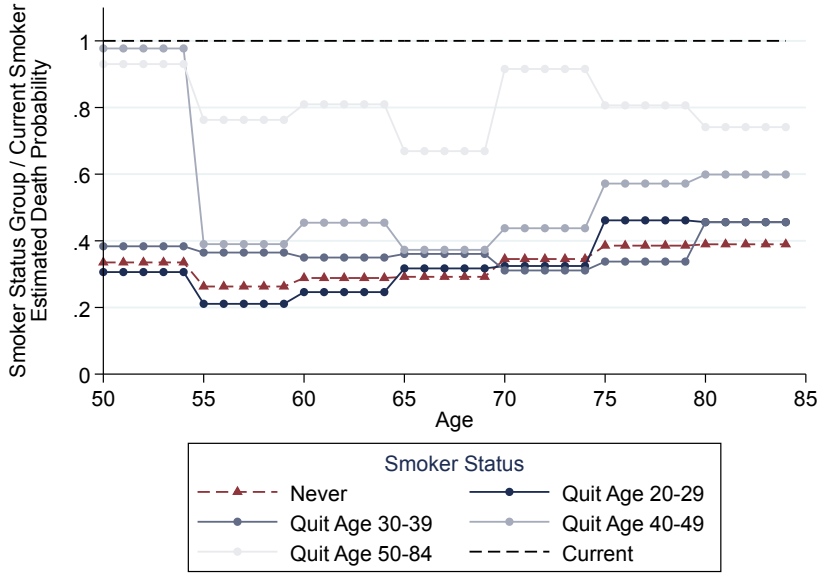

*Notes:* The shares are estimated using 2010-2019 data from the NHIS.

Figure J4: Share of Current Smokers Wanting to Quit by Age and Income Group



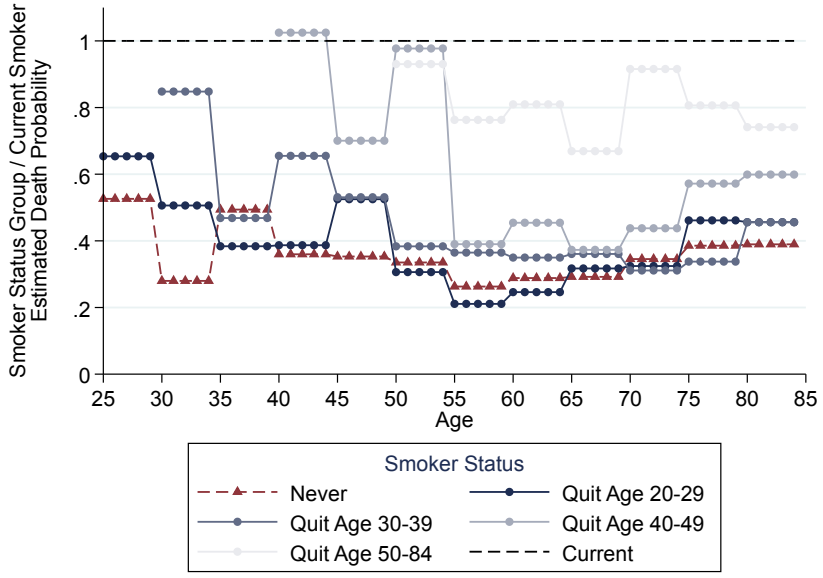

*Notes:* The shares are estimated using 2010-2019 data from the NHIS.

Figure J5: Mortality of Former and Never Smokers Relative to Current Smokers




*Notes:* One-year death probabilities are estimated using 2010-2019 data from the NHIS. The ratios are averaged across five-year bins.

Figure J6: Mortality of Former and Never Smokers Relative to Current Smokers, All Ages




*Notes:* One-year death probabilities are estimated using 2010-2019 data from the NHIS. The ratios are averaged across five-year bins.

**Evolution Over Time.** We use the 1997-2005 and 2010-2018 waves of the NHIS to track the evolution of the friction over time, presenting the evolution of $S_j$, $F_j$, $L_j$, $S_j \cdot F_j \cdot L_j$ over time in Table D1. The table also decomposes

how $L_j$ evolves over time. Lacking additional information on changes in mortality reductions due to smoking, we assume that the health costs are constant over time, only adjusting the foregone earnings by wage inflation (using estimates provided by the Economic Policy Institute (2026)). The changes in the monetary costs of smoking have increased due to an increase in the average cost of cigarettes, per BLS (2026).

## J.4 Additional Health Frictions

Table J5 uses the NHIS to determine the rate at which other potential health frictions are committed. We do not have reliable data on the mortality impact of these frictions, so we do not model them, although they could also be significant.

Table J5: Summary of $F$ for Additional Health Frictions

| | Not Taking an Influenza Vaccine ($F$) | Not Screening for Breast Cancer ($F$) | Not Screening for Cervical Cancer ($F$) |
|---|---|---|---|
| Low Income | 0.407 | 0.394 | 0.388 |
| Middle Income | 0.312 | 0.275 | 0.322 |
| High Income | 0.249 | 0.213 | 0.260 |

# Appendix K. Life Cycle Model

## K.1 Additional Model Details

This section provides a more complete description of the life cycle model described in Section 4.

**Demographics.** Time is discrete and indexed by $t \in \{t_0, T\}$. Age evolves according to:

$$a_{it} = a_{it-1} + 1. \tag{13}$$

Prior to the terminal age $a_T$, individuals face mortality risk:

$$D_{it} = \begin{cases} 0 & \text{with probability } \mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i) \\ 1 & \text{with probability } 1 - \mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i) \end{cases} \tag{14}$$

where $\mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i)$ denotes the probability of survival to the next period. The effective family size is:

$$n_{it} = (1 + \alpha_k \times \text{kids}(a_{it}, e_i))^{\alpha_n} \tag{15}$$

where $\alpha_k$ is the child weight and $\alpha_n$ is the equivalence scale exponent.

**Income Process.** Individual income depends on employment status:

$$y_{it} = \begin{cases} \max\left\{\exp\left(\overline{y}(\delta_i, e_i) + f(a_{it}, e_i, \delta_i) + z_{it} + \epsilon_{it}\right), \underline{y}\right\} & \text{if } a_{it} < a_R \text{ and } \zeta_{it} = E \\ \max\left\{\ell \cdot \exp\left(\overline{y}(\delta_i, e_i) + f(a_{it}, e_i, \delta_i) + z_{it}\right), \underline{y}\right\} & \text{if } a_{it} < a_R \text{ and } \zeta_{it} = U \\ 0 & \text{if } a_{it} \geq a_R \end{cases} \tag{16}$$

When employed, individuals receive transitory income shocks $\epsilon_{it}$ discretized from a mean-zero normal distribution with standard deviation $R_E(a_{it}, e_i)$. Employment status transitions according to:

$$\zeta_{it+1} = \begin{cases} E & \text{with probability } 1 - p_U(z_{it}, \zeta_{it}; e_i, \mathbf{f}_i) \\ U & \text{with probability } p_U(z_{it}, \zeta_{it}; e_i, \mathbf{f}_i) \end{cases} \tag{17}$$

with initial condition $\zeta_{i0} = E$. The persistent component of income evolves according to:

$$z_{it} = \begin{cases} z_{i0} & \text{if } a_{it} = 0, \quad z_{i0} \sim N(0, Q_0(e_i)^2) \\ \rho_z(e_i) \cdot z_{it-1} + \eta_{it} & \text{if } 0 < a_{it} < a_R \\ z_{it-1} & \text{if } a_{it} \geq a_R \end{cases} \tag{18}$$

where the innovation has a state-dependent distribution $\eta_{it} \sim N\left(B(\zeta_{it}; e_i),\ Q(\zeta_{it}; a_{it}, e_i)^2\right)$.

**Savings.** The liquid account balance has the following law of motion:

$$L_{it} = \begin{cases} L_{i0} \sim F_L(\cdot \mid e_i) & \text{if } a_{it} = 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i))\left(R^f + \tau^0_L\right) & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) < 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i)) \cdot R^{\theta,\text{net}}_{it} & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) \geq 0 \end{cases} \tag{19}$$

subject to a borrowing limit $S^L_{it} \geq -\underline{L}(a_{it}, e_i, \delta_i)$, where $\underline{L}(\cdot)$ is proportional to the deterministic component of income during working life, is frozen at its $a_R - 1$ value during retirement, and is zero at the terminal age.

When saving, individuals earn the after-tax return $R^{\theta,\text{net}}_{it}$ that depends on a blended capital gains tax rate. Define the regular income tax rate as $\tau_{\text{reg}}(\text{AGI}) = \mathscr{T}_y(\text{AGI})/\text{AGI}$ and the preferential capital gains tax rate $\tau_{\text{pref}}(\text{AGI})$ as a step function. The share of income subject to preferential rates is $\omega_{\text{pref}}(\text{AGI})$. The combined tax rate on capital gains is:

$$\tau_{\text{cap}}(\text{AGI}) = \tau_{\text{reg}}(\text{AGI}) \cdot (1 - \omega_{\text{pref}}(\text{AGI})) + \tau_{\text{pref}}(\text{AGI}) \cdot \omega_{\text{pref}}(\text{AGI}) \tag{20}$$

and the after-tax rate of return is $R^{\theta,\text{net}}_{it} = 1 + (1 - \tau_{\text{cap}}) \cdot (R^{\theta}_{it} - 1)$. Capital losses are capped at $\overline{\mathscr{L}}_{\text{cap}}$ for tax purposes.

The illiquid account balance has the following law of motion:

$$X_{it+1} = \begin{cases} 0 & \text{if } a_{it} = 0 \\ R^{\theta}_{it+1}\left(X_{it} + S^X_{it}\right) & \text{if } a_{it} \geq a_R \\ R^{\theta}_{it+1}\left(X_{it} + S^X_{it} \cdot (1 + \phi_x(a_{it}))\right) & \text{if } \zeta_{it} = E \text{ and } S^X_{it} < 0 \\ R^{\theta}_{it+1}\left(X_{it} + S^X_{it} + y_{it} \cdot m_x \cdot \min\left\{\frac{S^X_{it}}{y_{it}},\ c_x\right\}\right) & \text{if } \zeta_{it} = E \text{ and } S^X_{it} \geq 0 \\ R^{\theta}_{it+1}\left(X_{it} \cdot \mathscr{V}(a_{it}, \tilde{y}_{it}) + S^X_{it} \cdot (1 + \phi_x(a_{it}))\right) & \text{if } \zeta_{it} = U \end{cases} \tag{21}$$

where the vesting rate upon job loss is $\mathscr{V}(a_{it}, \tilde{y}_{it}) = 1 - p_{\text{vest}}(a_{it}, \tilde{y}_{it}) \times v_{\text{cond}}$, and $\tilde{y}_{it}$ denotes the persistent deterministic component of income $\exp(\overline{y}(\delta_i, e_i) + f(a_{it}, e_i, \delta_i) + z_{it})$. Total contributions in the employed-positive case are capped at $\overline{x}_{\text{total}}(a_{it})$. Contribution constraints are:

$$S^X_{it} \in \begin{cases} \{0\} & \text{if } I^X_i = 0 \\ [-X_{it},\ 0] & \text{if } a_{it} \geq a_R \\ \left[-\frac{X_{it}}{1+\phi_x(a_{it})},\ \overline{x}(a_{it})\right] & \text{if } \zeta_{it} = E \\ \left[-\frac{X_{it} \cdot \mathscr{V}(a_{it}, \tilde{y}_{it})}{1+\phi_x(a_{it})},\ 0\right] & \text{if } \zeta_{it} = U \end{cases} \tag{22}$$

**Portfolio Choice.** There are two assets: a risk-free bond with gross return $R^f$ and a risky stock with return:

$$R^s_{t+1} = R^f \cdot \exp\left(\mu_s + \epsilon^s_{t+1}\right), \quad \epsilon^s_{t+1} \sim N(0, \sigma^2_{rs}) \tag{23}$$

An individual's portfolio return is $R^\theta_{it} = R^f + \theta_{it-1}\left(R^s_t - R^f\right)$.

**Transfers and Taxes.** Social security benefits are a piecewise linear function of approximate average indexed yearly earnings, following Catherine (2022):

$$T^{ss}_{it} = \mathscr{T}_{ss}(\widehat{\text{AIYE}}_i) \cdot \mathbf{1}_{a_{it} \geq a_R} \tag{24}$$

where $\widehat{\text{AIYE}}_i = \text{AE}(e_i, \delta_i, z_{it:a_{it}=a_R-1})$ approximates average lifetime earnings from the individual's persistent income in their final year of working life. Individuals receive EITC benefits $T^{\text{eitc}}_{it} = \widehat{\text{EITC}}(a_{it}, y^T_{it})$ during working life (zero in retirement) and SNAP benefits $T^{\text{snap}}_{it} = \widehat{\text{SNAP}}(a_{it}, \hat{y}^{\text{gross}}_{it})$, where $\hat{y}^{\text{gross}}_{it} = y_{it}$ during working life and $\hat{y}^{\text{gross}}_{it} = T^{ss}_{it}$ in retirement. Each is a polynomial approximation of the respective federal formula with age-group-specific coefficients. In retirement, individuals have access to SSI:

$$T^{\text{ssi}}_{it} = \begin{cases} \max\{\overline{y}_{\text{ssi}} - T^{ss}_{it}, 0\} & \text{if } a_{it} \geq a_R \text{ and } W_{it} < \overline{W}_{\text{ssi}} \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

Individuals receive inheritances $T^I_{it} = \max\{\text{poly}_3(a_{it}; e_i), 0\}$ and repay student debt according to:

$$T^{sd}_{it} = \begin{cases} \min\left\{\frac{D(e_i, \mathbf{f}_i)\cdot(r_d - 1)}{1 - r_d^{-T_d}}, y_{it}\right\} & \text{if } a_{it} < T_d \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

where $r_d = R^f + \Delta_d$ is the student debt interest rate and $D(e_i, \mathbf{f}_i)$ is the debt principal. Taxable income is:

$$y^T_{it} = \begin{cases} T^{ss}_{it} - S^X_{it} & \text{if } a_{it} \geq a_R \\ \max\{y_{it} - S^X_{it}, 0\} & \text{if } a_{it} < a_R \end{cases} \tag{27}$$

where 401(k) contributions are tax-deductible. Income tax payments are $T^y_{it} = \mathscr{T}_y\left(y^T_{it}\right)$. The government ensures a consumption floor $\underline{c}$ via a transfer $T^{\text{floor}}_{it}$. Total transfers are:

$$T_{it} = T^{\text{eitc}}_{it} + T^{\text{snap}}_{it} + T^{\text{ssi}}_{it} - T^y_{it} + T^{ss}_{it} + T^I_{it} - T^{sd}_{it} + T^{\text{floor}}_{it}. \tag{28}$$

**Preferences.** Flow utility is:

$$U(c_{it}, a_{it}) = \frac{n_{it}}{1-\gamma}\left(\frac{c_{it}}{n_{it}}\right)^{1-\gamma} \tag{29}$$

where $\gamma$ is the coefficient of relative risk aversion. Bequest utility follows De Nardi et al. (2010):

$$U_B(W_{it}) = \frac{n_{it} \cdot \psi_1}{1-\gamma} \left( \frac{b_{it}}{n_{it}} \right)^{1-\gamma} \tag{30}$$

where $\psi_1$ controls the strength of the bequest motive and $b_{it} = \psi_2 + W_{it} - \left[ \mathcal{T}_y(y_{\text{heir}} + X_{it}) - \mathcal{T}_y(y_{\text{heir}}) \right] \cdot \mathbf{1}_{I_i^X = 1}$ is the bequeathable amount.

## K.2 Recursive Formulation

Denote the vector of non-friction state variables as $\mathbf{x}_{it}$ and the value function as $V(\mathbf{x}_{it}, \mathbf{f}_i)$. Because individuals correctly account for their frictions, continuation values are evaluated using the value function at the individual's own friction vector. The value function is:

$$V(\mathbf{x}_{it}, \mathbf{f}_i) = \begin{cases} U_B(W_{it}) & \text{if } a_{it} = a_T \\ \max_{S_{it}^L, S_{it}^X, \theta_{it}} \mathscr{B}(\mathbf{x}_{it}, \mathbf{f}_i, S_{it}^L, S_{it}^X, \theta_{it}) & \text{otherwise} \end{cases} \tag{31}$$

where the Bellman equation is:

$$\mathscr{B}(\cdot) = U(c_{it}, a_{it}) + \beta \cdot \left[ \mathscr{D}_{it} \cdot \mathbf{E}_{it}\big(V(\mathbf{x}_{it+1}, \mathbf{f}_i)\big) + (1 - \mathscr{D}_{it}) \cdot \mathbf{E}_{it}\big(U_B(W_{it+1})\big) \right]$$

subject to: (13)–(28) and

$$c_{it} + \left(S_{it}^L - L_{it}\right) + S_{it}^X = y_{it} + T_{it}$$

$$S_{it}^L \geq -\underline{L}(a_{it}, e_i, \delta_i)$$

$$S_{it}^X \in [\underline{S}_{it}^X, \overline{S}_{it}^X]$$

The expected continuation value $\mathbf{E}_{it}(V(\mathbf{x}_{it+1}, \mathbf{f}_i))$ is computed by integrating over next period's employment status, persistent income innovations, transitory income shocks, and stock return innovations. The expected bequest utility $\mathbf{E}_{it}(U_B(W_{it+1}))$ integrates over stock return innovations only.

## K.3 Mapping Empirical Friction Estimates to Model Permanent States

This section describes how we map the empirical friction estimates from Table 3 onto the model's permanent states, as summarized in Section 4. For each friction $j$, the empirical estimates are computed in bins of an observable income measure that varies across frictions (for example, education groups for the college attendance friction).[4] The model's permanent states for frictions are the three permanent income groups, sometimes interacted with the four education groups. The goal of the mapping is to translate each friction probability $F_j$ — and,

[4] The health frictions are the one exception that cannot be mapped using this procedure: because the external simulation requires a mortality process as an input, and the mortality process itself depends on the health frictions, friction prevalence must be known before the external simulation can be run. Therefore, we assign the health frictions directly using the estimates of $F_j$ by permanent income group from Table 3.

for the direct dollar loss frictions, the per-period loss $\lambda_j$ — from the observable bins onto the model's permanent states.

The mapping proceeds in three steps. First, we run a simulation in which we draw a panel of individuals, assign each to an education group and permanent income group according to the calibrated population shares, and simulate ages and labor income forward using the same demographic process, mortality schedule, and income process as in the life cycle model, but without solving the model. Second, for each friction $j$, we compute the conditional distribution of the model's permanent states given the observable bin in the simulated panel. Let the observable have $K$ bins indexed by $k$ and let the permanent states have $M$ categories indexed by $m$. We construct the $K \times M$ matrix $A$ with entries $A_{km}$ equal to the share of simulated individuals in observable bin $k$ who fall into permanent state $m$ such that each row of $A$ sums to one. Finally, we project the empirical estimates onto the model's permanent states using the following equation:

$$\widehat{\mathbf{f}}_j = \left(A^\top A\right)^{-1} A^\top \mathbf{f}_j, \tag{32}$$

which correspond to the OLS coefficient of the bin-level empirical probabilities on the share of individuals in each permanent state within each observable bin. For the direct dollar loss frictions, we apply the same projection to the share at risk $S_j$ and to the per-period dollar loss $L_j$, and then construct the per-period loss in the model as $\widehat{\lambda}_j = \widehat{S}_j \cdot \widehat{L}_j$.

## K.4 Constructing Baseline Mortality Probabilities

Let $q_j(a)$ denote the observed death probability at age $a$ for permanent income group $j$. Since these probabilities already reflect the elevated mortality of individuals that are subject to the health frictions that enter the model, we construct counterfactual death probabilities $\tilde{q}_j(a)$ that remove the contribution of these frictions. The resulting probabilities serve as the baseline mortality distribution in the model. In the remainder of this section, we describe how we construct these probabilities.

Within each income group $j$ and age $a$, the population can be partitioned according to whether individuals have elevated mortality due to each of the two frictions. For smoking, the elevated-mortality group at ages $a \geq 50$ comprises both optimal smokers ($o_j^{\text{smoke}}(a)$) and suboptimal or late-quitting smokers ($S_j^{\text{smoke}}(a) \cdot F_j^{\text{smoke}}(a)$), while those without elevated smoking mortality either never smoked or quit before age 50.[5] These smoking shares are estimated from the NHIS by income group and smoothed using a quartic polynomial in age. Because the NHIS smoking shares are estimated for ages 50–84 while the mortality schedule extends beyond age 84, we hold the age-84 smoking shares fixed for all older ages rather than extrapolating the quartic beyond the estimation sample. For ages $a < 50$, we set the share of elevated smoking mortality to zero, since the smoking mortality penalty in the model is also zero before age 50.

[5] Recall that $S_j^{\text{smoke}}$ is the share of the population at risk (smokers who want to quit plus former smokers who quit before 50) and $F_j^{\text{smoke}}$ is the share of this group that fails to quit. Optimal smokers ($o_j^{\text{smoke}}$) are outside the at-risk group entirely, since they do not intend to quit. The remaining group, $S_j^{\text{smoke}} \cdot (1 - F_j^{\text{smoke}})$, are successful quitters who stopped by age 50 and do not have elevated mortality.

For statins, we use the age-varying elevated-mortality share constructed in the main text. We combine the NHIS age-specific share with high cholesterol and the income-group-specific non-take-up estimates described in Section 2.6.1. The resulting share is $S_j^{\text{statin}}(a) \cdot F_j^{\text{statin}}$. These age-varying inputs are computed in five-year age bins, with the 80+ bin applied to all ages 80 and older.

We denote these two marginal elevated-mortality shares by:

$$\begin{aligned} p_j^{\text{smoke}}(a) &= S_j^{\text{smoke}}(a) \cdot F_j^{\text{smoke}}(a) + o_j^{\text{smoke}}(a), \\ p_j^{\text{statin}}(a) &= S_j^{\text{statin}}(a) \cdot F_j^{\text{statin}}. \end{aligned} \tag{33}$$

The age-varying shares used in (33) are distinct from the scalar prevalence estimates used for friction assignment in the model described in Section 4.2, which are age-invariant. For smoking, the scalar prevalence estimates $S_j^{\text{smoke}}$, $F_j^{\text{smoke}}$, and $o_j^{\text{smoke}}$ are reported in Table J4 and evaluated at age 50. For statins, the scalar prevalence estimate is reported in Table 3.

We denote $R_j^{\text{smoke}}(a)$ as the mortality ratio of the elevated-smoking-mortality group relative to the baseline group, which takes one value for ages 50–74 and another for ages 75+; these income-group-specific ratios are reported in Table J4. We denote $R^{\text{statin}}$ as the all-cause mortality ratio implied by the statin estimate, which does not vary by income group. For statins, we set $R^{\text{statin}}$ equal to one plus the product of the cardiovascular mortality effect discussed in Section 2.6.1 and the 56.9 percent share of deaths due to cardiovascular disease reported there.

To allow these two elevated-mortality indicators to be correlated, we generate them using the same tetrachoric-correlation structure described in Section 2.7. Specifically, let $Z_i(a, j) \sim \mathcal{N}(0, \Sigma)$, where $\Sigma$ has unit diagonal elements and off-diagonal elements equal to the target tetrachoric correlations across smoking and statins. In the current implementation, this off-diagonal correlation is set to zero. For each $k \in \{\text{smoke}, \text{statin}\}$, define:

$$H_i^k(a) = \mathbf{1}\left\{ Z_i^k(a, j) \leq \Phi^{-1}\left( p_j^k(a) \right) \right\}. \tag{34}$$

Under multiplicative mortality effects at the individual level, the factor by which the two frictions inflate population mortality is:

$$D_j(a) = \mathbb{E}_\Sigma \left[ \left( R_j^{\text{smoke}}(a) \right)^{H_i^{\text{smoke}}(a)} \left( R^{\text{statin}} \right)^{H_i^{\text{statin}}(a)} \right], \tag{35}$$

where the expectation is taken over the latent normal distribution. Thus, for all ages $a$:

$$\tilde{q}_j(a) = \frac{q_j(a)}{D_j(a)}. \tag{36}$$

In the model, individuals with the smoking friction face death probability $\tilde{q}_j(a) \cdot R_j^{\text{smoke}}(a)$, and individuals with the statin friction face death probability $\tilde{q}_j(a) \cdot R^{\text{statin}}$, with these factors multiplying when both mortality frictions are present. For smoking, this implementation follows the convention that the model's smoking prevalence is $S_j^{\text{smoke}} \cdot F_j^{\text{smoke}} + o_j^{\text{smoke}}$, while the floor prevalence that remains in the smoking counterfactual is $o_j^{\text{smoke}}$. For statins, the friction is assigned at the age-averaged prevalence $S_j^{\text{statin}} \cdot F_j^{\text{statin}}$ from Table 3 and treated as permanent, while

the multiplier $R^{\text{statin}}$ is fixed across ages. This implicitly assumes friction-holders have high cholesterol at all ages, while empirically the share with high cholesterol is age-varying. Because both the multiplier and the share with high cholesterol at young ages are small, this approximation has limited impact on simulated outcomes.

## K.5 Additional Tables and Figures

Table K1: Model Results: Lifetime Friction Impact (Levels)

| Income Group | $\Delta R_{sum}$ | $\Delta$Consumption$_{sum}$ | $\Delta\sum$Wealth$_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta$Survival$_{65}$ |
|---|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | | |
| Low | \$8,298 | \$7,311 | \$674 | \$908 | 0.000 pp |
| Middle | \$18,610 | \$17,265 | \$3,551 | \$4,029 | 0.000 pp |
| High | \$9,696 | \$9,086 | \$2,110 | \$2,245 | 0.000 pp |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | | |
| Low | \$4,017 | \$3,897 | \$87 | \$117 | 0.000 pp |
| Middle | \$4,858 | \$4,710 | \$620 | \$703 | 0.000 pp |
| High | \$1,344 | \$1,292 | \$254 | \$270 | 0.000 pp |
| *Panel C: Not Investing in Stock Mutual Funds* | | | | | |
| Low | \$26,768 | \$22,330 | \$5,962 | \$8,034 | 0.000 pp |
| Middle | \$55,082 | \$45,101 | \$16,326 | \$18,526 | 0.000 pp |
| High | \$0 | \$0 | \$0 | \$0 | 0.000 pp |
| *Panel D: Saving in Low Interest Accounts* | | | | | |
| Low | \$1,077 | \$1,013 | \$85 | \$114 | 0.000 pp |
| Middle | \$1,024 | \$1,292 | -\$612 | -\$695 | 0.000 pp |
| High | -\$1,533 | -\$708 | -\$1,581 | -\$1,682 | 0.000 pp |
| *Panel E: Investing in Individual Stocks* | | | | | |
| Low | -\$57 | -\$41 | -\$4 | -\$6 | 0.000 pp |
| Middle | -\$97 | \$188 | -\$588 | -\$667 | 0.000 pp |
| High | \$1,901 | \$1,670 | -\$364 | -\$388 | 0.000 pp |
| *Panel F: Investing in High-Fee Mutual Funds* | | | | | |
| Low | \$4,486 | \$3,706 | \$1,040 | \$1,401 | 0.000 pp |
| Middle | \$24,722 | \$19,980 | \$7,598 | \$8,621 | 0.000 pp |
| High | \$82,522 | \$66,836 | \$28,267 | \$30,073 | 0.000 pp |

Continued on next page

**Table K1 – continued from previous page**

| Income Group | $\Delta R_{sum}$ | $\Delta$Consumption$_{sum}$ | $\Delta\sum$Wealth$_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta$Survival$_{65}$ |
|---|---|---|---|---|---|
| *Panel G: Paying Late Fees and Paying Overdraft Fees* | | | | | |
| Low | \$6,915 | \$6,693 | -\$179 | -\$241 | 0.000 pp |
| Middle | \$11,214 | \$11,719 | -\$1,202 | -\$1,364 | 0.000 pp |
| High | \$2,432 | \$2,555 | -\$358 | -\$381 | 0.000 pp |
| *Panel H: Choosing Dominated Health Insurance* | | | | | |
| Low | \$34 | \$30 | \$16 | \$21 | 0.000 pp |
| Middle | \$5,532 | \$5,358 | \$477 | \$542 | 0.000 pp |
| High | \$4,520 | \$4,379 | \$460 | \$489 | 0.000 pp |
| *Panel I: Not Claiming EITC Benefits* | | | | | |
| Low | \$4,669 | \$4,545 | \$48 | \$65 | 0.000 pp |
| Middle | \$649 | \$769 | -\$266 | -\$302 | 0.000 pp |
| High | -\$445 | -\$297 | -\$455 | -\$484 | 0.000 pp |
| *Panel J: Not Claiming SNAP Benefits* | | | | | |
| Low | \$12,848 | \$12,316 | -\$221 | -\$298 | 0.000 pp |
| Middle | \$2,040 | \$2,588 | -\$1,504 | -\$1,706 | 0.000 pp |
| High | -\$1,280 | -\$735 | -\$1,922 | -\$2,045 | 0.000 pp |
| *Panel K: Not Taking Statin Medications* | | | | | |
| Low | \$3,979 | \$4,234 | \$472 | \$250 | 0.671 pp |
| Middle | \$5,515 | \$6,263 | \$1,513 | \$800 | 0.231 pp |
| High | \$5,866 | \$7,450 | \$1,996 | \$1,075 | 0.104 pp |
| *Panel L: Failing to Quit Smoking* | | | | | |
| Low | \$27,970 | \$29,047 | \$1,682 | \$442 | 3.150 pp |
| Middle | \$32,028 | \$37,676 | \$7,224 | \$2,868 | 1.334 pp |
| High | \$19,442 | \$23,727 | \$5,449 | \$2,761 | 0.299 pp |
| *Panel M: All Frictions* | | | | | |
| Low | \$103,817 | \$98,241 | \$10,689 | \$11,657 | 3.760 pp |

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**Table K1 – continued from previous page**

| Income Group | $\Delta R_{sum}$ | $\Delta\text{Consumption}_{sum}$ | $\Delta\sum\text{Wealth}_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta\text{Survival}_{65}$ |
|---|---|---|---|---|---|
| Middle | \$170,232 | \$160,728 | \$36,035 | \$34,211 | 1.535 pp |
| High | \$124,526 | \$115,746 | \$33,565 | \$31,499 | 0.403 pp |

*Notes:* Panels A–L report the average lifetime impact of removing a single friction, expressed in dollar levels. Panel M reports the impact of simultaneously removing all frictions. All variables with subscript $sum$ denote undiscounted lifetime sums. $\Delta R_{sum}$ is the change in the undiscounted lifetime sum of current-period consumable income, as defined in (11). $\Delta\text{Consumption}_{sum}$ is the change in the undiscounted lifetime sum of consumption. Let $W_{i65}$ denote total wealth (liquid plus 401(k) assets) for individual $i$ at age 65, and let $N_j$ denote the number of simulated individuals in permanent income group $j$. $\Delta\sum\text{Wealth}_{65}$ is $(\sum_i W_{i65}^{\text{cf}} - \sum_i W_{i65}^{\text{base}})/N_j$, assigning zero wealth in a scenario if an individual is not alive at age 65. $\Delta\overline{\text{Wealth}}_{65}$ is the difference in average $W_{i65}$ among individuals alive at age 65 in each scenario. $\Delta\text{Survival}_{65}$ is the change in the probability of being alive at age 65 within the income group, expressed in percentage points. See Table 6 for the corresponding percent changes.

Table K2: Model Results: Per-Period Friction Impact

| Observed Income Group ($j$) | $S_j \times F_j$ | $L_j$ | $\Delta_j$ | $\Delta_j / \overline{R}_j$ |
|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | |
| Low | 0.187 | $802 | $150 | 0.686% |
| Middle | 0.086 | $3,003 | $260 | 0.582% |
| High | 0.036 | $8,435 | $306 | 0.346% |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | |
| Low | 0.060 | $1,364 | $81 | 0.372% |
| Middle | 0.028 | $2,755 | $76 | 0.170% |
| High | 0.011 | $1,781 | $19 | 0.021% |
| *Panel C: Not Investing in Stock Mutual Funds* | | | | |
| Low | 0.388 | $795 | $308 | 1.411% |
| Middle | 0.231 | $2,993 | $690 | 1.548% |
| High | 0.093 | $7,210 | $673 | 0.762% |
| *Panel D: Saving in Low Interest Accounts* | | | | |
| Low | 0.635 | $26 | $16 | 0.075% |
| Middle | 0.580 | $9 | $5 | 0.012% |
| High | 0.498 | -$4 | -$2 | -0.002% |
| *Panel E: Investing in Individual Stocks* | | | | |
| Low | 0.031 | $196 | $6 | 0.028% |
| Middle | 0.048 | $213 | $10 | 0.023% |
| High | 0.060 | $49 | $3 | 0.003% |
| *Panel F: Investing in High-Fee Mutual Funds* | | | | |
| Low | 0.911 | $146 | $133 | 0.610% |
| Middle | 0.910 | $446 | $406 | 0.909% |
| High | 0.908 | $1,628 | $1,478 | 1.672% |
| *Panel G: Paying Late Fees and Paying Overdraft Fees* | | | | |
| Low | 0.379 | $390 | $147 | 0.675% |
| Middle | 0.333 | $443 | $148 | 0.331% |
| High | 0.210 | $450 | $94 | 0.107% |
| *Panel H: Choosing Dominated Health Insurance* | | | | |
| Low | 0.616 | $49 | $30 | 0.137% |
| Middle | 0.515 | $154 | $79 | 0.178% |
| High | 0.409 | $200 | $82 | 0.093% |
| *Panel I: Not Claiming EITC Benefits* | | | | |

Continued on next page

**Table K2 – continued from previous page**

| Observed Income Group ($j$) | $S_j \times F_j$ | $L_j$ | $\Delta_j$ | $\Delta_j / \overline{R}_j$ |
|---|---|---|---|---|
| Low | 0.210 | $387 | $81 | 0.372% |
| Middle | 0.212 | $22 | $5 | 0.010% |
| High | 0.214 | -$24 | -$5 | -0.006% |
| *Panel J: Not Claiming SNAP Benefits* | | | | |
| Low | 0.583 | $405 | $236 | 1.082% |
| Middle | 0.581 | $24 | $14 | 0.031% |
| High | 0.580 | -$30 | -$17 | -0.020% |
| *Panel K: Not Taking Statin Medications* | | | | |
| Low | 0.161 | $446 | $72 | 0.328% |
| Middle | 0.144 | $579 | $83 | 0.186% |
| High | 0.132 | $939 | $124 | 0.141% |
| *Panel L: Failing to Quit Smoking* | | | | |
| Low | 0.182 | $2,853 | $519 | 2.376% |
| Middle | 0.127 | $3,599 | $457 | 1.025% |
| High | 0.092 | $5,211 | $481 | 0.545% |
| *Panel M: All Frictions* | | | | |
| Low | · | · | $1,813 | 8.302% |
| Middle | · | · | $2,330 | 5.223% |
| High | · | · | $3,373 | 3.818% |

*Notes:* Panels A–L report the per-period impact of removing each friction separately, while Panel M reports the impact of removing all frictions simultaneously. Rows correspond to groups defined at each age and within each aggregate shock path using prior-year pre-tax pre-transfer income in the baseline simulation: the bottom 25 percent, middle 50 percent, and top 25 percent. We exclude the first simulated age, for which prior-year simulated income is unavailable. We calculate $S_j \times F_j$, $L_j$, and $\Delta_j$ in Panels A–L from the realized baseline and counterfactual simulations following Definitions 2 and 3. For Panel M, $\Delta_j$ is computed directly, while $S_j \times F_j$ and $L_j$ are not separately defined. Following the approach in column (3) of Table B1, we construct $\overline{R}_j$ by first averaging baseline consumable income across all observed ages for each individual observed at least twice and then averaging these person-level values across the age-specific income-group observations. The resulting values are $21,835, $44,602, and $88,347 for the low-, middle-, and high-income groups, respectively.

Table K3: Model Results: Per-Period Friction Impact by Permanent Income Group

| Permanent Income Group ($j$) | $S_j \times F_j$ | $L_j$ | $\Delta_j$ | $\Delta_j / \overline{R}_j$ |
|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | |
| Low | 0.199 | $781 | $155 | 0.906% |
| Middle | 0.099 | $3,174 | $313 | 0.689% |
| High | 0.026 | $5,773 | $153 | 0.181% |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | |
| Low | 0.072 | $1,050 | $75 | 0.438% |
| Middle | 0.030 | $2,719 | $82 | 0.180% |
| High | 0.004 | $5,217 | $21 | 0.025% |
| *Panel C: Not Investing in Stock Mutual Funds* | | | | |
| Low | 0.466 | $1,076 | $502 | 2.921% |
| Middle | 0.272 | $3,406 | $926 | 2.039% |
| High | 0.000 | · | $0 | 0.000% |
| *Panel D: Saving in Low Interest Accounts* | | | | |
| Low | 0.655 | $31 | $20 | 0.118% |
| Middle | 0.616 | $28 | $17 | 0.038% |
| High | 0.436 | -$55 | -$24 | -0.029% |
| *Panel E: Investing in Individual Stocks* | | | | |
| Low | 0.017 | -$62 | -$1 | -0.006% |
| Middle | 0.048 | -$34 | -$2 | -0.004% |
| High | 0.067 | $449 | $30 | 0.036% |
| *Panel F: Investing in High-Fee Mutual Funds* | | | | |
| Low | 0.913 | $92 | $84 | 0.490% |
| Middle | 0.910 | $457 | $416 | 0.915% |
| High | 0.907 | $1,435 | $1,301 | 1.543% |
| *Panel G: Paying Late Fees and Paying Overdraft Fees* | | | | |
| Low | 0.385 | $337 | $130 | 0.755% |
| Middle | 0.398 | $473 | $188 | 0.415% |
| High | 0.106 | $361 | $38 | 0.045% |
| *Panel H: Choosing Dominated Health Insurance* | | | | |
| Low | 0.660 | $1 | $1 | 0.004% |
| Middle | 0.558 | $167 | $93 | 0.205% |
| High | 0.325 | $219 | $71 | 0.084% |
| *Panel I: Not Claiming EITC Benefits* | | | | |

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**Table K3 – continued from previous page**

| Permanent Income Group ($j$) | $S_j \times F_j$ | $L_j$ | $\Delta_j$ | $\Delta_j / \overline{R}_j$ |
|---|---|---|---|---|
| Low | 0.211 | \$414 | \$87 | 0.510% |
| Middle | 0.212 | \$52 | \$11 | 0.024% |
| High | 0.213 | -\$33 | -\$7 | -0.008% |
| *Panel J: Not Claiming SNAP Benefits* | | | | |
| Low | 0.583 | \$413 | \$241 | 1.402% |
| Middle | 0.579 | \$59 | \$34 | 0.076% |
| High | 0.584 | -\$35 | -\$20 | -0.024% |
| *Panel K: Not Taking Statin Medications* | | | | |
| Low | 0.172 | \$435 | \$75 | 0.434% |
| Middle | 0.146 | \$633 | \$93 | 0.204% |
| High | 0.123 | \$751 | \$93 | 0.110% |
| *Panel L: Failing to Quit Smoking* | | | | |
| Low | 0.215 | \$2,440 | \$524 | 3.052% |
| Middle | 0.135 | \$3,976 | \$538 | 1.185% |
| High | 0.066 | \$4,634 | \$307 | 0.363% |
| *Panel M: All Frictions* | | | | |
| Low | · | · | \$1,945 | 11.330% |
| Middle | · | · | \$2,861 | 6.300% |
| High | · | · | \$1,964 | 2.328% |

*Notes:* Panels A–L report the per-period impact of removing each friction separately, while Panel M reports the impact of removing all frictions simultaneously. Rows correspond to the model's permanent income groups, which are constructed from individual income fixed effects estimated in the PSID: the bottom 25 percent, middle 50 percent, and top 25 percent of the fixed-effect distribution. An individual's permanent income-group assignment is fixed over their life and held fixed when comparing the baseline and counterfactual outcomes. We calculate $S_j \times F_j$, $L_j$, and $\Delta_j$ in Panels A–L from the realized baseline and counterfactual simulations following Definitions 2 and 3. For Panel M, $\Delta_j$ is computed directly, while $S_j \times F_j$ and $L_j$ are not separately defined. Following the approach in column (3) of Table B1, we construct $\overline{R}_j$ by first averaging baseline consumable income across all observed ages for each individual observed at least twice and then averaging these person-level values within each permanent income group. The resulting values are \$17,168, \$45,417, and \$84,362 for the low-, middle-, and high-income groups, respectively.

Table K4: Alternative Counterfactual: Lifetime Friction Impact from Equalizing Friction Prevalence to High Income

| Income Group ($j$) | $\Delta R_{sum}$ | $\Delta$Consumption$_{sum}$ | $\Delta\sum$Wealth$_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta$Survival$_{65}$ |
|---|---|---|---|---|---|
| *Panel A: Not Attending College Due to Frictions* | | | | | |
| Low | 0.041% | 0.037% | 0.104% | 0.104% | 0.000% |
| Middle | 0.068% | 0.065% | 0.113% | 0.113% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel B: Attending 2-Year For-Profit Colleges* | | | | | |
| Low | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Middle | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel C: Not Investing in Stock Mutual Funds* | | | | | |
| Low | 2.991% | 2.479% | 18.882% | 18.882% | 0.000% |
| Middle | 2.069% | 1.745% | 5.305% | 5.305% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel D: Saving in Low Interest Accounts* | | | | | |
| Low | 0.037% | 0.036% | 0.083% | 0.083% | 0.000% |
| Middle | 0.014% | 0.017% | -0.044% | -0.044% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel E: Investing in Individual Stocks* | | | | | |
| Low | -0.026% | -0.032% | 0.627% | 0.627% | 0.000% |
| Middle | -0.002% | -0.008% | 0.038% | 0.038% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel F: Investing in High-Fee Mutual Funds* | | | | | |
| Low | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Middle | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel G: Paying Late Fees and Paying Overdraft Fees* | | | | | |
| Low | 0.558% | 0.536% | -0.421% | -0.421% | 0.000% |
| Middle | 0.308% | 0.332% | -0.291% | -0.291% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |

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**Table K4 – continued from previous page**

| Income Group ($j$) | $\Delta R_{sum}$ | $\Delta$Consumption$_{sum}$ | $\Delta\sum$Wealth$_{65}$ | $\Delta\overline{\text{Wealth}}_{65}$ | $\Delta$Survival$_{65}$ |
|---|---|---|---|---|---|
| *Panel H: Choosing Dominated Health Insurance* | | | | | |
| Low | 0.001% | 0.002% | 0.044% | 0.044% | 0.000% |
| Middle | 0.086% | 0.086% | 0.063% | 0.063% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel I: Not Claiming EITC Benefits* | | | | | |
| Low | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Middle | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel J: Not Claiming SNAP Benefits* | | | | | |
| Low | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Middle | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel K: Not Taking Statin Medications* | | | | | |
| Low | 0.131% | 0.136% | 0.486% | 0.231% | 0.254% |
| Middle | 0.026% | 0.031% | 0.056% | 0.027% | 0.029% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel L: Failing to Quit Smoking* | | | | | |
| Low | 3.780% | 3.904% | 6.509% | 1.293% | 5.150% |
| Middle | 1.009% | 1.219% | 1.972% | 0.694% | 1.269% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| *Panel M: All Frictions* | | | | | |
| Low | 7.511% | 7.152% | 26.740% | 20.269% | 5.380% |
| Middle | 3.588% | 3.508% | 7.297% | 5.926% | 1.294% |
| High | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |

*Notes:* This table is analogous to Table 6, except that the counterfactual equalizes the removable friction probability $F_j$ within each low- and middle-income group to the corresponding high-income value rather than removing the friction entirely. For composite friction keys, only the income-group component is replaced, so education or access status is preserved. The high-income group is unchanged by construction, so its entries are zero. See the notes to Table 6 for outcome definitions, including the definitions of $\Delta\sum$Wealth$_{65}$ and $\Delta\overline{\text{Wealth}}_{65}$.

Table K5: Alternative Counterfactual: Effects of Equalizing Friction Prevalence to High Income on Total Inequality

| Friction | $R_{sum}$ | $\text{Consumption}_{sum}$ | $\text{Wealth}_{65}$ | | | $\text{Wealth}_{65}$ \| Counterfactual $\text{Survival}_{65}=1$ | | |
|---|---|---|---|---|---|---|---|---|
| Inequality Metric | Gini | Gini | P25 | P75 | $\frac{P75-P25}{P50}$ | P25 | P75 | $\frac{P75-P25}{P50}$ |
| Value in Baseline | 0.4123 | 0.4033 | $33,012 | $594,869 | 2.9261 | · | · | · |
| *Panel A: Level Change in Inequality Metric* | | | | | | | | |
| Not Attending College Due to Frictions | -0.0001 | -0.0001 | $73 | $117 | -0.0020 | $73 | $117 | -0.0020 |
| Attending 2-Year For-Profit Colleges | 0.0000 | 0.0000 | $0 | $0 | 0.0000 | $0 | $0 | 0.0000 |
| Not Investing in Stock Mutual Funds | -0.0022 | -0.0017 | $4,693 | $18,969 | -0.1149 | $4,693 | $18,969 | -0.1149 |
| Saving in Low Interest Accounts | -0.0000 | -0.0000 | $142 | -$375 | -0.0018 | $142 | -$375 | -0.0018 |
| Investing in Individual Stocks | 0.0001 | 0.0000 | -$45 | $173 | 0.0015 | -$45 | $173 | 0.0015 |
| Investing in High-Fee Mutual Funds | 0.0000 | 0.0000 | $0 | $0 | 0.0000 | $0 | $0 | 0.0000 |
| Paying Late Fees and Paying Overdraft Fees | -0.0009 | -0.0009 | -$331 | -$1,012 | 0.0121 | -$331 | -$1,012 | 0.0121 |
| Choosing Dominated Health Insurance | -0.0001 | -0.0001 | $81 | -$13 | -0.0027 | $81 | -$13 | -0.0027 |
| Not Claiming EITC Benefits | 0.0000 | 0.0000 | $0 | $0 | 0.0000 | $0 | $0 | 0.0000 |
| Not Claiming SNAP Benefits | 0.0000 | 0.0000 | $0 | $0 | 0.0000 | $0 | $0 | 0.0000 |
| Not Taking Statin Medications | -0.0001 | -0.0001 | -$60 | -$393 | -0.0002 | $143 | $34 | -0.0036 |
| Not Quitting Smoking | -0.0041 | -0.0043 | -$1,519 | -$4,684 | 0.0349 | $2,728 | $5,975 | -0.0707 |
| All Frictions | -0.0074 | -0.0072 | $3,106 | $14,689 | -0.0709 | $7,483 | $25,729 | -0.1808 |
| *Panel B: Percent Change in Inequality Metric* | | | | | | | | |
| Not Attending College Due to Frictions | -0.024% | -0.023% | 0.220% | 0.020% | -0.070% | 0.220% | 0.020% | -0.070% |
| Attending 2-Year For-Profit Colleges | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Not Investing in Stock Mutual Funds | -0.529% | -0.422% | 14.217% | 3.189% | -3.928% | 14.217% | 3.189% | -3.928% |
| Saving in Low Interest Accounts | -0.003% | -0.002% | 0.429% | -0.063% | -0.062% | 0.429% | -0.063% | -0.062% |
| Investing in Individual Stocks | 0.015% | 0.010% | -0.136% | 0.029% | 0.050% | -0.136% | 0.029% | 0.050% |
| Investing in High-Fee Mutual Funds | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Paying Late Fees and Paying Overdraft Fees | -0.222% | -0.227% | -1.001% | -0.170% | 0.414% | -1.001% | -0.170% | 0.414% |
| Choosing Dominated Health Insurance | -0.035% | -0.035% | 0.245% | -0.002% | -0.091% | 0.245% | -0.002% | -0.091% |
| Not Claiming EITC Benefits | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Not Claiming SNAP Benefits | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% | 0.000% |
| Not Taking Statin Medications | -0.033% | -0.035% | -0.182% | -0.066% | -0.008% | 0.435% | 0.006% | -0.123% |
| Not Quitting Smoking | -0.990% | -1.062% | -4.601% | -0.787% | 1.192% | 9.483% | 1.023% | -2.333% |
| All Frictions | -1.789% | -1.774% | 9.408% | 2.469% | -2.422% | 26.133% | 4.407% | -5.956% |

*Notes:* This table is analogous to Table 7, except that the counterfactual equalizes the removable friction probability $F_j$ within each low- and middle-income group to the corresponding high-income value rather than removing the friction entirely. For composite friction keys, only the income-group component is replaced, so education or access status is preserved. The high-income group is unchanged by construction. See the notes to Table 7 for outcome definitions, inequality-statistic definitions, and calculation details.