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

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Abstract

We provide the first systematic quantification of how decision-making frictions—such as failing to claim government benefits, choosing dominated insurance plans, not saving for retirement, and not quitting smoking—aggregate to affect inequality in income, consumption, and wealth. We review the existing literature and combine it with original analysis of survey data to estimate the prevalence and financial impact of 17 frictions across the income distribution. To make these frictions comparable, we develop a common 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. Aggregating across all frictions, the estimated impact on annual income is 9.3% for the bottom quartile of the income distribution relative to 2.6% for the top quartile; the total loss for low-income households is seven times larger than the impact of a major EITC expansion. We then incorporate these frictions into a life cycle model with realistic institutional features, including tax-advantaged retirement accounts, progressive taxation, portfolio choice, and a social insurance system. The model reveals that removing frictions tends to reduce inequality in lifetime consumption, with the largest effects coming from smoking and attending for-profit colleges. Our results suggest that decision-making frictions are a quantitatively important contributor to inequality across a range of economic outcomes.

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A large 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 that decision-making frictions—such as limited self-control, inattention, and limited cognition—influence 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 17 frictions spanning education choices, savings, borrowing, insurance, benefit claiming, and health behaviors. We develop a common 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—that we estimate separately for three income groups: low (bottom 25%), middle (25%–75%), and high (top 25%). 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 income, consumption, and wealth. Our primary focus is on inequality across households within the bulk of the distribution, rather than households in the very top of the distribution.

The first part of the paper aims to summarize the evidence on the financial impact of key behavioral frictions. Building also on consulting a range of domain experts, we focus on the 17 frictions listed in Table 1. This list is by no means exhaustive, and not everyone will agree that each of these constitutes a behavioral friction as opposed to an optimizing decision subject to time or monetary costs. Nonetheless, we think there is value in a first systematic attempt to address this question and to establish a framework for doing so.

We develop a framework, described in detail in the next section, in which each friction is characterized by three parameters estimated separately for each income group: the share at risk s_j, the friction prevalence f_j, and the average loss conditional on being affected L_j. For each friction, we estimate these parameters using a combination of prior literature and original analysis of 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 per-person impact of each friction on each income group, which we use to make losses comparable across frictions.

We find that decision-making frictions disproportionately affect lower-income individuals, both in prevalence and as a share of income; the complete set of estimates is reported in Table 2. Aggregating across all frictions, the estimated impact on annual income is approximately 9.3% for the low-income group relative to approximately

Table 1: Decision-Making Frictions

No.	Category	Friction	Section
1	Education	Not Attending College	Section 2.1
2	Education	Attending 2-Year For-Profit Colleges	Section 2.2
3	Savings	Not Meeting the Employer 401(k) Match	Section 3.1
4	Savings	Not Investing in the Stock Market	Section 3.2
5	Savings	Under-Diversification	Section 3.2
6	Savings	Investing in High-Fee Mutual Funds	Section 3.2
7	Borrowing	Not Refinancing a Mortgage	Section 4.1
8	Borrowing	Suboptimal Credit Card Debt Repayment	Section 4.2
9	Borrowing	Paying Late Fees	Section 4.3
10	Borrowing	Paying Overdraft Fees	Section 4.4
11	Insurance	Choosing Dominated Insurance Plans	Section 5.1
12	Insurance	Suboptimally Lapsing Life Insurance	Section 5.2
13	Benefits	Not Claiming EITC Benefits	Section 6.1
14	Benefits	Not Claiming SNAP Benefits	Section 6.2
15	Health	Not Taking Statin Medications	Section 7.1
16	Health	Not Screening for Colon Cancer	Section 7.2
17	Health	Smoking	Section 7.3

2.6% for the high-income group. The frictions with the largest impact on low-income households as a share of income include not claiming SNAP benefits, not attending college, smoking, and not investing in the stock market. For high-income households, the largest frictions in dollar terms are under-diversification and excessive mutual fund fees. To put these magnitudes in perspective, we benchmark them against the effects of several policy reforms. We find that the total loss for the low-income group is approximately seven times larger than the income effect of all states implementing a 25% EITC supplement, a major expansion of one of the largest anti-poverty programs in the United States. 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 our empirical approach is that it analyzes each friction in isolation, and therefore does not require assumptions about (i) the correlation of frictions across individuals, (ii) the correlation between frictions and underlying individual characteristics that drive income, or (iii) the extent to which different frictions interact with one another in affecting income. In the second part of the paper, we complement this analysis with a structural life cycle model. While this approach inherently involves more assumptions, it has the benefits of allowing us to model some of the frictions directly, quantify the lifetime impacts of each friction, and—by endogenizing consumption-savings decisions—study effects on consumption and wealth inequality.

The life cycle model that we build has institutionally realistic features of the choice environment faced by US households, including income and employment risk, tax-advantaged retirement savings accounts, portfolio choice, mortgage debt, unsecured debt, and a tax and social insurance system. We incorporate each friction for a share f_j of households calibrated to match our estimates. We model the effects of a friction based on its type, which falls into one of two categories. The first category comprises frictions that affect decisions modeled explicitly, such

as 401(k) savings, portfolio choice, or college attendance. 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 life insurance lapsation, smoking, or preventative healthcare. For these frictions, we calibrate the effect on model variables—such as income, wealth, or mortality—using our estimates from the first part of the paper.

We estimate the impact of each friction by conducting counterfactuals in which we turn off each friction independently, holding all other frictions at their baseline prevalence, and study the effects on lifetime income, consumption, and wealth. The effects of removing each friction by income group are reported in Table 5. 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 percent gains in lifetime consumption for lower-income households. For example, removing the for-profit college friction raises lifetime consumption by approximately 0.6% for the low-income group relative to 0.3% for the high-income group, and the education and smoking frictions generate a similar pattern. The direct dollar loss frictions—such as dominated insurance, overdraft fees, and late fees—also generate larger percent effects for lower-income households, consistent with the empirical evidence on their prevalence across the income distribution.

We also present results for population-wide measures of inequality in Table 6, examining changes in distributional statistics such as Gini coefficients (for lifetime income and consumption) and interquartile 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 in the current version of the paper. Nevertheless, we find that removing frictions tends to reduce inequality in lifetime income and consumption, consistent with the fact that frictions disproportionately reduce the resources of lower-income households. The frictions with the largest effects on consumption inequality are smoking and attending for-profit colleges, both of which are concentrated among lower-income individuals. The effects on wealth inequality are more nuanced, as the benefits of removing many frictions scale with income or wealth. An important caveat is that these wealth inequality results depend crucially on the assumption that individuals are fully aware of the frictions they face and account for them when making consumption-saving decisions; we plan to relax this assumption in future drafts of the paper. Additionally, we plan to 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 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 large and growing literature studying inequality in income and wealth. As discussed above, almost none of this work incorporates behavioral frictions. Our contribution is to provide a comprehensive accounting of the role that decision-making frictions play in shaping the distribution of income, consumption, and wealth across the income distribu-

tion.[1]

Second, we contribute to the literature on behavioral household finance, which has documented frictions in a wide range of financial decisions (see Beshears et al. 2018a and Gomes et al. 2021 for reviews). While this literature has studied individual frictions in depth, it has not attempted to quantify how these frictions aggregate across domains or to assess their implications for inequality. Our contribution is to bring these frictions together within a common framework and to study their collective impact. However, it is important to recognize that our approach to doing so 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. This approach allows us to build a tractable model that contains all of the frictions jointly, but limits our ability to draw welfare conclusions. Second, 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 subject to a friction hold a small share of aggregate wealth.

Third, we contribute to the very large literature that builds life cycle models of household behavior to study positive and normative questions. Beginning with Gourinchas and Parker (2002), this literature has built increasingly rich quantitative models that incorporate a wide range of institutional features—such as portfolio choice, housing, retirement accounts, and social insurance—in order to match various patterns in household behavior. Our contribution is to bring a broad set of behavioral frictions into a life cycle model and to study their collective implications for inequality. 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 specifically 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; the section in which each friction is discussed is indicated in Table 1. Section 8 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 the following section, and counterfactual results are presented in Section 10. Section 11 concludes.

1 Framework for Estimating Friction Impacts

In this section, we describe a general conceptual framework that clarifies the empirical objects we seek to measure. Consider a continuum of individuals denoted by i that are observed at age t and belong to an income group $j \in \{L, M, H\}$.[2] Empirically, L, M, and H correspond to individuals in the bottom 25%, middle 50%, and top 25% of the

[1] 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).

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

lifetime income distribution. We denote an arbitrary friction by $\mathbf{f}_{it} \in \{0,1\}$, where $\mathbf{f}_{it} = 1$ means that individual i at age t is subject to a particular friction in Table 1. We use the term "friction" broadly: it could be an explicit mistake due to, e.g., a self-control problem, or it could reflect an optimal choice given imperfect information.

Our primary goal is to estimate the effect of each friction on inequality in income, wealth, and consumption across the three income groups. We take two complementary approaches to doing this: a purely empirical approach that relies on fewer assumptions, and a structural life cycle model. Our first approach—described in the remainder of this section—attempts to measure the effects on individuals' current resources from setting $\mathbf{f}_{it} = 0$ for *all* individuals, where by current resources we mean the total amount of cash-on-hand prior to making intertemporal consumption-savings decisions.

Formally, we refer to these current resources as "income" (abusing terminology for brevity) defined as

$$\text{Income}_{it}(\mathbf{f}_{it}) = \Big(\text{Labor Income}_{it}(\mathbf{f}_{it}) + \text{Capital Income}_{it}(\mathbf{f}_{it}) + \text{Benefits}_{it}(\mathbf{f}_{it}) - \text{Taxes}_{it}(\mathbf{f}_{it}) - \ell_{j(i)t}\mathbf{f}_{it}\Big) \cdot D_{it}(\mathbf{f}_{it}), \quad (1)$$

where $\ell_{j(i)t}$ is any direct dollar loss associated with the friction of interest and $D_{it}(\mathbf{f}_{it}) \in \{0,1\}$ is an indicator for whether an individual is alive. Different frictions affect current income through different channels. For example, not attending college due to frictions reduces Labor Income$_{it}$; paying credit card late fees represents a direct dollar loss through $\ell_{j(i)t}$; and smoking affects income through its effect on mortality, D_{it}. At the individual level, we can compute the impact of the friction on current income as

$$L_{it}(\mathbf{f}_{it}) = \text{Income}_{it}(0) - \text{Income}_{it}(\mathbf{f}_{it}). \quad (2)$$

Computing $L_{it}(\mathbf{f}_{it})$ requires knowing whether an individual is subject to a particular friction: if they are, $L_{it}(\cdot)$ will generally be positive, and zero otherwise. Among individuals in group j that are subject to the friction, we define the following key terms:

Definition 1. *For each friction and income group $j \in \{L, M, H\}$, at a given age t:*

1. *The **share affected**, s_{jt}, is the share of individuals in group j for which the friction is relevant:*

$$s_{jt} = \mathbb{P}\left(\mathbf{f}_{it} > 0 \mid j(i) = j\right). \quad (3)$$

2. *The **friction prevalence**, f_{jt}, is the share of individuals that are subject to the friction, conditional on it being relevant:*

$$f_{jt} = \mathbb{E}\left(\mathbf{f}_{it} \mid \mathbf{f}_{it} > 0, j(i) = j\right). \quad (4)$$

3. *The **average loss**, L_j, is the average loss in current income across all individuals and ages in group j that are subject to the friction:*

$$L_j = \mathbb{E}\left(L_{it}(\mathbf{f}_{it}) \mid \mathbf{f}_{it} = 1, j(i) = j\right). \quad (5)$$

We use s_j and f_j to denote averages of s_{jt} and f_{jt} across ages. For the majority of frictions, we assume perfect persistence in who is subject to the friction—the same individuals have $\mathbf{f}_{it} = 1$ in every period—and so $f_j = f_{jt}$ for all t. Under these assumptions, we can aggregate the per-period loss over a lifetime by computing the unconditional average annual loss from the friction in group j as $s_j \cdot f_j \cdot L_j$. We measure the effect of a friction on inequality by comparing $s_H \cdot f_H \cdot L_H$ with $s_L \cdot f_L \cdot L_L$.

In the following sections, we go through each friction in Table 1 and describe in detail how we compute s_j, f_j, and L_j, grouping frictions into categories based on the specific behavior that they affect. The corresponding results are shown in Table 2, with an overview of our computation for each friction shown in Table 3. We then summarize the evidence across all the frictions in Section 8.

An important benefit of this empirical approach is that it analyzes each friction in isolation, and therefore does not require assumptions about (i) the correlation of frictions across individuals (e.g., whether individuals who smoke are also more likely to pay late fees), (ii) the correlation between frictions and underlying individual characteristics that drive income (e.g., ability or preferences), or (iii) the extent to which different frictions interact with one another in affecting income. In the final part of the paper, we incorporate each of these frictions into a structural life cycle model. While this analysis inherently requires taking a stand on each of these dimensions, we view it as complementary for three main reasons. First, translating all of the frictions in this section into income losses requires several assumptions that we can relax in the life cycle model by modeling some of the frictions directly. Second, the model allows us to quantify the dynamic impacts of each friction over the course of individuals' entire life cycles. Finally, through endogenizing consumption-savings decisions, our model allows us to study the effects on consumption and wealth inequality.

2 Education Frictions

2.1 Not Attending College

To estimate the impact of this friction, we aim to estimate three main parameters: (i) the average returns to attend (higher-quality) college; (ii) the share of low-income students impacted by these frictions; (iii) the share of high-income students impacted by these frictions. We premise that it is difficult to clearly separate the impact of behavioral frictions from the impact of financial friction; we present an attempt to do so.

Returns to College Attendance. We start from 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 three main papers to identify the return for the marginal college attender largely from low-income groups. Zimmerman (2014) estimates a (intent-to-treat) 22 percent return 7 years after the college admission, estimated for admission to Florida college using a regression discontinuity design. Similarly, Smith et al. (2025) for Georgia estimates a 17 percent return to attending a 4-year public college by age 30 using a regression discontinuity estimator based on SAT score; notably, the estimate in the paper is higher (around 30%) for low-income students. Additionally, Mountjoy (2025) also uses a regression

discontinuity design based on the SAT and ACT score for admission into 4-year (selective) public colleges in Texas and estimate an (intent-to-treat) return to attending the selective public colleges of 8.6 log points in years 8-12 after admission. The different estimates are actually quite consistent, as the three papers all estimate returns of 9-11 percent per extra year of college attended, with the differences due to the fact that in Mountjoy (2025) the students barely to the right of the admission threshold attend on average just 1 year of extra college, while the students to the right of the admission threshold in Zimmerman (2014) gain on average 3 years of schooling.

One way to aggregate the results in the various papers in the literature is to assume that behavioral frictions cause students to miss on average 1.5 years of extra college schooling, leading to a loss L_j of 15 percent in earnings. We think that this is a fairly conservative estimate, corresponding approximately also to the unweighted average across the estimates in the various papers. (If we were to assume that frictions deter the full 4 years of college attendance, the loss would be closer to 40 percent.) We will assume also an amount of additional debt and lost earnings due to college attendance, as detailed below.

College Attendance by Income Group. The other key parameter for the model is the share of people that do not attend college due to a behavioral friction among low-income, middle-income, and high-income individuals. (For education choices, the income grouping refers necessarily to parental income.) We present a combination of pieces of evidence which we then combine into a number.

A motivating piece of evidence suggesting differences by parental income is that, even conditioning on test scores, or grades, the rates of college attendance differ significantly by income proxies. 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.

An important issue is how such difference responds to various controls for grades in school and other characteristics. In Table A1 we use the 2009 High School Longitudal Survey (HSLS) and regress attendance to any college on parental income groups, with a variety of controls. Comparing the high-income group to the low-income group, in Column 2, controlling for academic GPA deciles, as well as deciles of a math cognitive test, we estimate a 12.7 percentage point difference in college attendance. Adding additional controls (Column 3) leads to a somewhat larger difference.[3] The estimate for the middle-income group (relative to the low-income group) is slightly less than half the size of the high-income group.

We acknowledge that this comparison takes into account both behavioral frictions as well as financial frictions to college attendance. We now summarize results from a couple experiments which point to behavioral frictions being important and of comparable magnitudes.

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. This had an 8 percentage point impact on college attendance one year later.

Dynarski et al. (2021) is an RCT which targets low-income, high-grades students in Michigan letting them know that they would have a free ride at the University of Michigan. The paper documents an 8 percentage point impact

[3] 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).

on enrollment and attendance at a 4-year selective college.

Mentoring programs during the senior year in high school (about 10 hours per student) have sizeable impacts too, for eg., Barr and Castleman (2025) document that a mentoring RCT during senior year in high school leads to a 9 percentage point increase in 4-year college enrollment. This is consistent also with Oreopoulos and Ford (2019) which finds a 9 percentage point increase in college enrollment in response to mentoring during the college application.[4]

Importantly, not all such interventions have a sizable impact. Indeed, most interventions in the US that provide just information lead to null result 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 which detect an impact 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 rather small compared to the lifetime returns.

The papers above identify at least three different types of 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 (and the literature has examples of other frictions). These factors operate largely independently, though there are overlaps, e.g., mentoring could certainly included FAFSA help. In our view, an overall measure should take into account the combined impact of these frictions. Each of the three papers documents above finds an 8 or 9 percentage point impact of the friction on college attendance.[5] One upper-case scenario would be to sum across them, leading to an estimate of a $8+8+9=25$ percentage point impact on the frictions on college attendance for low-income individuals. We prefer to give a more conservative number and assume a 10 percentage point estimate. Given that the proportion not attending college (s_j) among the low-income students is 0.491, the implied share with a friction (f_j) is guessed to be $0.10/0.491 = 0.204$.

We note that the estimate above can be seen as conservative in that they do not include other behavioral frictions that also stand in the way of higher education attainment, e.g., the evidence of Hastings and Weinstein (2008) and Cohodes et al. (2025) for middle-school students.

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) as specified by L_j. Table 2 provides a summary of the estimates, including an average annual loss due to the friction, taking into account the impact on future earnings, debt, and foregone early earnings.

Notes and Caveats. There are a number of caveats to this analysis. First, we do not get a single estimate from a paper about the share of individuals with a friction, but aim to aggregate across papers, which we recognize involves some arbitrariness; we aimed to pick a relatively conservative estimate. Second, we acknowledge that it is hard to draw a firm line between behavioral frictions and frictions that have a cost component. Third, we do not have an estimate of the prevalence of the friction for the middle- and high-income group so we assume it is the

[4] 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).

[5] 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.

same as for the low-income group. Fourth, 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 that the college wage premium would be reduced. Fifth, we have multiple estimates of return to attending college over the next 5-10 years, but no long-term estimates of the returns; we assume that the returns to college are permanent.

2.2 Attending 2-Year For-Profit Colleges

We first determine the proportion of students attending 2-year colleges using data from the 2011-2019 PSID. Next, we determine the proportion of students attending for-profit colleges, conditional on attending a 2-year college, using data from the National Center for Education Statistics (NCES, Snyder et al. (2019)) and the 2012/17 Beginning Postsecondary Students survey (BPS, 2017). Snyder et al. (2019) provides us with overall college enrollment by parental income group, and the BPS (2017) provides us with for-profit college enrollment conditional on attending college (also by parental income group). Table A2 presents the combined estimates for college enrollment. The table shows that in the low-income group, 8.0% of students go to a 2-year for-profit college[6], while in the high-income group, the same percent is only 2.4%. The attendance to a 2-year public or non-profit college is instead fairly similar across income groups (Column 2). Thus, as Column 3 shows, the share of 2-year college attendance that is to a for-profit college is much higher for low-income students (0.231) than for high-income students (0.091). This is our estimate of the behavioral friction f_j. For comparison, Column 4 shows that attendance to 4-year colleges is steeply increasing in parental income.

We estimate the impact of 2-year for-profit college attendance, compared to community college attendance, following Cellini and Turner (2019). This paper used administrative data, merged with 1999-2014 IRS tax data, to study outcomes of federally aided students who exited post-secondary institutions between 2006 and 2008. Their main empirical result is 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) 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, and ii) students who attended a for-profit college are 1.5 percentage points less likely to be employed and, conditional on employment, have an income that is 11.3 log points less than others who attended a public/non-profit college. In dollar terms, they lose $2,144 annually.

Additional Evidence. We identify two additional papers in the literature comparing outcomes between for-profit colleges and community colleges. 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 $1,936 less in 2009 (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

[6] For example, Snyder et al. (2019) indicated that 65.4% of all low parental income children went to college and BPS (2017) indicated that among all low parental income children who went to college, 6.9% went to a private 2-year for-profit college and 5.4% went to a private less-than-2-year for-profit college. We calculate $0.654 * (6.9 + 5.4)/100$ to get 0.080.

on $6,428 more in loans and, 6 years after graduating, make $8,541.20 (or 36.27%) less than their public sector counterparts. Overall, these estimates are remarkably consistent with the estimates in Cellini and Turner (2019).

Altogether, the key parameters for the model are shown in table 2. For the share of consumers at risk, we take the share attending 2-year colleges (of any type) from the PSID. We take the share s_j with the friction f_j as computed in table A2 using the Cellini and Turner (2019) evidence. Finally, we estimate the average annual loss L_j combining the evidence on earnings loss, higher unemployment probability and higher debt.

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 does indicate if anything that the earnings loss increase 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 be a better match for a subset of students.

3 Savings Frictions

3.1 Not Meeting the Employer 401(k) Match

[Subsection on 401ks is work in progress] Retirement savings in the form of Defined Contributions such as 401(k)s are, together with home equity, the most important form of illiquid assets held by households in the US. An important factor is that 401(k) plans have a tax-advantage status, with contributions pre-tax and taxation at withdrawal, and no taxation on capital gains. In addition, the large majority of employers that offer 401(k)s provide an employer match, most typically in the form of a 50 percent match on each dollar contributed up to 6 percent contributions. Given these tax 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, participation on 401(k) plans is partial and affected by factors such as the default at sign up. These default effect suggest that lack of participation in 401(k)s, at least to an extent, are due to behavioral frictions such as procrastination and limited attention. We present details below.

Evidence. A number of papers starting from Madrian and Shea (2001); Choi et al. (2004) document that the participation in 401(k) plans depends significantly on the default. With an opt-out default, participation in the 401(k) plan at six month is typically 90 percent, while with an opt-in default the participation at six month is typically around 50 percent, implying a 40 percentage point default effect. The default choice is also reflected in the participation on the intensive margin, with 3 percent participation, the typical default, being the most common choice for plans with opt-out default.[7] The magnitude of the default effects tends to be larger for employees with lower pay (Madrian and Shea, 2001), suggesting a larger friction for low-income workers.

The large difference in participation as function of the default attenuates significantly over time, as individuals

[7] A 3 percent participation does not take full advantage of the match, usually set to go until 6 percent.

in the opt-in default increase their participation over time (Choukhmane, 2025), though a difference in participation is often still detectable 2 years since the start of the employment.

To estimate quantitatively the extent of the 401(k) friction, we first measure the share s_j of the population eligible for the 401(k) decision, that is, workers employed in companies that offer a 401(k) plan, using data from Myers et al. (2024). The share of workers eligible for a 401(k) is 0.46 in the low-income group and 0.74 in the low-income group.

Next, we obtain estimates for the proportion of workers contributing to a 401(k) plan conditional on eligilibity, which we take the measure of $1 - f_j$. We use administrative W-2 data from Choukhmane et al. (2023) as well as from Myers et al. (2024). Table * below summarizes the estimate for f_j by income group. Our estimates range from a ~40% baseline contribution rate among the lowest income x education group to a ~70% baseline contribution rate among the highest income x education group. These estimates also roughly align with the data in Madrian and Shea (2001), where participation rates ranged from 20% to 80% with no default contribution.

We measure the loss L_j due to lack of participation with an approximation. We compute the amount lost due to the forgone match, not taking into account the tax advantages, by computing the match for a 6 percent contribution.

3.2 Poor Portfolio Choice

There is a vast literature in individual finance on behavioral frictions for individual investors, (Campbell, 2006; Beshears et al., 2018b; Gomes et al., 2021). Relative to this literature, our coverage of behavioral frictions has to necessarily be selective. We focus on three frictions which have played a central role in the literature, all regarding poor portfolio choices that translate into lower financial returns. The first friction is limited participation in the stock market. Given the consistent equity premium over the last century in the US, not participating leads to significantly lower returns to savings. The second friction is a failure to hold an efficient portfolio due to *under-diversification*, defined as holding a small number of individuals stocks rather than mutual funds (Goetzmann and Kumar, 2008). A third friction is the choice of *mutual funds with high fees*. Identical funds, for example S&P 500 funds, can differ in their fees by 100 basis points or more, and the fees are typically shrouded, making it hard for investors to target low-fee funds. As Choi et al. (2010) shows, individuals seem to pay no attention to the fees in their choice even among funds that are identical except for the fee.

We acknowledge a variety of other behavioral frictions which impact the portfolio returns, such as the disposition effect, over-trading and home bias. We hope that future work will build on this work by adding more portfolio frictions.

3.2.1 Not Investing in the Stock Market

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. Of course, lack of participation in equity markets could also be due to a

number of other factors, such as lack of savings or fixed costs to invest. To partially address these points, we define the friction only for individuals with savings above a threshold.

To measure the key parameters, 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 1 month of pre-tax salary and $1,000 (given fixed costs for investment in equity). Figure 1a plots the share of the population satisfying these conditions by age and income group. Not surprisingly, the share with savings above the threshold 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 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.[8] Table 2 below reports the prevalence for each of the three income groups. The lack of stock market participation is very high for the low-income group, at around 60 percent, and is much lower for the high-income group, at around 10-20 percent.

To measure the impact L_j of the friction, we need a counterfactual for the share invested in the stock market. In the model, as detailed below, we address that with evidence from Choukhmane and de Silva (2026). For this reduced-form evaluation, we take as counterfactual the share invested in equity by consumers with positive stock market participation. We estimate a share of 41 percent for the low-income and the middle-income group, and 43 percent for the high-income group. To estimate the loss per individual with no equity participation, we multiply this share first by the average equity premium (assumed to be 5.5 percent as in Gomes (2020)), and second by the average financial wealth (including DC wealth).[9] Table 2 reports the average estimated loss. The magnitude is sizable, at $262 for the low-income group, and $2,541 for the high-income group.

Notes and Caveats. We made a set of assumptions designed in general to take a conservative measure of the impact of this friction. 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.

3.2.2 Under-Diversification

A tenet of portfolio choice is that investors should build well-diversified portfolio to avoid incurring idiosyncratic risk. And yet individuals investors often pick individual stocks to be part of their equity holding. For example, Goetzmann and Kumar (2008) documents how common under-diversification is among US investors using data from the 1990s, and how it is correlated with other biases in investment. Using Dutch data, Gaudecker (2015) documents a similar large extent of under-diversification, and measures the implied losses using a CAPM framework.

There are two important caveats to these findings. In the last two decades, the choice of mutual funds has

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

[9] We winsorize individual losses at the 95 percent level to avoid the impact of possible outliers, as can be seen in Figure C1.

become more common, compared to the choice of individual stocks, so the extent of under-diversification measured in Goetzmann and Kumar (2008) likely overstates its importance in the 2010s and later. Second, the choice of individual stocks is uncommon among Defined Contribution plans, which account for much of equity holdings for US individuals.

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 \$1,000 or one month of income. Figure 1b shows the share as function of the income group and age. The share is between 30 and 60 percent (depending on the 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 1b 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 how we measure the loss L_j from the under-diversification. 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 the assumption that the stocks are randomly selected, the expected return on this portfolio equals the market's expected return, so all of the loss will come from an increase in volatility, which, under the CAPM, we can 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 this into a dollar loss by multiplying the certainty-equivalent return reduction by the dollar equity holdings of individual stocks (see Section C in the appendix for the full derivation). We winsorize the dollar losses at the 95th percentile to avoid the impact of outliers, as illustrated in Figure C2.

Table 2 shows that the loss is sizable. To give a sense of the components that yield the estimate of the loss, consider the estimate for the middle-income group. In this group, for the share that has positive savings and is under-diversified (that is, $s_j = f_j = 1$) the average investment in individual equity is \$45,000. Given this number, we compute the loss due to excess volatility (winsorized at the 95 percent) as outlined above to be \$2,686.

Notes and Caveats. Like for other frictions, we aim to make a set of conservative assumptions. We set the threshold for the friction at an investment in individual stocks of at least 50% of the individual wealth. In practice, this does not matter too much as setting a lower threshold adds individuals who tend to have a relatively small loss. Table C1 and Table C2 provide robustness checks on our definitions of under-diversification. We also exclude from the friction the choice of individual stocks in DC plans, such as the choice of employer stock. The latter investment used to be common, but has become less common following the passage of the Pension Protection Act of 2006, which required employers to allow workers to move their stock into diversified options and also, through introducing QDIAs, led to the growth of target date funds as the common default option (Parker et al., 2025).

3.2.3 Excessive Mutual Fund Fees

Over time, individuals investors have over time shifted more of their investment towards mutual funds. While this limits, to an extent, the losses due to under-diversification, it opens the door to a different category of losses due to the choice of mutual funds. Specifically, the literature has documented that consumers are very insensitive to the amount of fees charged on mutual funds, and that funds with high fees are common, even among retirement plans. Since fees are deducted from fund returns, investors who choose high-fee funds are reaping predictably lower returns. 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 inexperienced investors not paying attention to the fees. This is further evidenced by Choi et al. (2010) using a laboratory experiment. In the experiment, participants choose among different S&P 500 mutual fund plans, each presented with realistic prospectus features. Even among MBA students, the choice of plan almost entirely disregards the mutual fund fee, with investors focusing instead on returns since inception (which can differ across plans due to different dates of inception). Contributing to this investor confusion is the fact that the fees are shrouded.

To measure the incidence of the choice of mutual funds with excessive fees, we first compute the share of investors with investments in mutual funds, including both non-retirement and retirement accounts. Figure 1c shows the incidence by age and income group. As expected, the share is significantly higher for the higher-income group, reaching 90 percent, and it peaks in late middle age. For the low-income group it hovers around 20 percent.

Next, we present a measure of the share of consumers with a behavioral friction, who would plausibly not pay attention to the fees. The evidence in Choi et al. (2010) suggests that nearly all investors are subject to it. Based on that evidence, we will assume that all consumers in all three income groups are affected, that is, $f_j = 1$. We recognize that this is not a conservative assumption but adopt it given the lack of additional evidence and computational advantages.[10]

To measure the extent of loss L_j for the investors that do not pay attention to fees, we need a measure of the average fee for mutual funds that consumers choose in excess of the minimal fee. This is the extra fee that on average consumers with the friction pay, given that they choose randomly with respect to fees. We use the mutual fund data base from CRSP from 2011 to 2019, computing for each fund category[11] the average fee in excess of the 10th percentile fund fee.[12] We then weight across the categories by the total net assets in each category to compute an average excess mutual fund fee of 40.73 basis points.[13]

We multiply this average excess fee by the total wealth invested in mutual funds to estimate the losses for each individual. We winsorize the losses at the 95th percentile, as illustrated in Figure C3. Table 2 reports the findings.

Notes and Caveats. As pointed out above, and unlike for other frictions, we approximate the friction assuming $f_j = 1$. Second, even within a narrow fund category, there can be variation in the exact investments, and investors

[10] Assuming $f_j = 1$ compared to, say, $f_j = 0.8$ comes at a significant computation gain as it allows us to have one less group to simulate, halving simulation time.

[11] We determine fund categories using the CRSP defined fund style codes.

[12] When computing the average fee and the 10th percentile fee, we weight by the total net assets of each fund in the category.

[13] This excess fee is much lower than the one documented in Hortaçsu and Syverson (2004), reflecting the stark decline in fees from the 1990s to the 2010s.

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, in Table C3 we compute the results using a more conservative computation of excess mutual fund fees, subtracting from the average fee the 20th percentile of fees (instead of the 10th).[14] The estimated loss is about 20 percent lower.

4 Borrowing Frictions

4.1 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). When households are inattentive, they will instead not refinance. We first measure using SCF data the share of households s_j for which this is relevant, that is, households with a fixed-rate mortgage. We then provide a measure from papers in the literature on the share f_j of households that are asleep. Finally, we compute the average loss L_j from not refinancing for households that are asleep. We then discuss how we then implement the mortgage refinancing decision within the life-cycle model.

This analysis is motivated by a number of papers who document the role of behavioral frictions in mortgage refinancing. Among others, Keys et al. (2016) use US data from a million mortgages from 2010 and shows that a significant number of US households do not refinance their mortgage, 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 also document inertia in refinancing and estimate a model with inertia and psychological costs.

Figure D2 reproduces a key finding of Andersen et al. (2020). 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. Assume for example that an household purchased a home in 2012 with interest rates at 4 percent and is considering refinancing in 2018 when interest rates are at 5 percent and assume fixed costs of 100 basis points (the average). In this case, there are negative incentives equal to -200 basis points, and we do not expect the household to refinance. Suppose now that the same investor consider refinancing in 2021, when interest rates are at 2 percent. In this case, the incentive would be positive at +100 basis points, and we would expect the household to refinance under the standard model.

The figure displays two pieces of evidence. The histogram bars display the distribution of the incentives across the sample. If households always refinanced whenever it makes economic sense to do so, the distribution would be censored on the right, as 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. This is the key finding

[14] The 10th percentile of fees is 9.41 basis points, the 20th percentile of fees is 16.27 basis points, and the mean is 50.14 basis points.

of failure to refinance the mortgage. The line displays complementary evidence. Namely, it shows the probability of refinancing in a given quarter as function of the incentives. We expect such probability to be zero for negative incentives, as is the case. But for positive incentives under the standard model we expect that probability to be close to 1; instead, it peaks at 12-13 percent for an incentive of 100 basis points and takes on lower values for larger incentives, indicating a high incidence of the behavioral inertia.[15]

Data. Using data from the SCF, we determine the share s_j of households at risk, proceeding as follows. For each income group and 5-year bin, we measure the share of households who own a house and have a (fixed-rate) mortgage. As Figure 1d reports, the share is inverse U-shaped in age, peaking around age 50. Importantly, home-ownership is significantly higher for the higher-income group than for the lower-income group, which is much more likely to be renting. The figure also displays a summary measure of the mortgage (in dollars) for households which take a new mortgage in that income-age bin, since it is an important parameter to document the losses. The mortgage size is significantly larger for higher-income households, as expected.

The second parameter is the share f_j of households with a mortgage who display a friction and do not refinance when it is optimal to do so. Andersen et al. (2020) assume that households have a probability p of being asleep in each quarter, which is i.i.d. over quarters. We take the estimate of Model 3 in Table 2 of Andersen et al. (2020) that the average probability of being asleep in a given quarter is 92%.[16] We additionally use the evidence in Figure 9a regarding the difference in such probability by income group. In particular, the asleep probability for the first quintile of income is higher by roughly 4 pp, and the asleep probability for the fifth quintile of income is lower by roughly 1 pp. Combining this, lower/middle/higher income households have an i.i.d. chance of 96%/92%/91% of being asleep in each quarter. In the table we report the probability that a given income group is asleep for a whole year, that is, p^4. For example, for the low-income group the estimated probability is $0.96^4 = 0.85$. We note that, unlike for other frictions where we model f_j as being the share of type that has a constant friction over time, in this case we assume that the friction is i.i.d., based on the evidence in Andersen et al. (2020).

The third parameter is the loss L_j in case of lack of refinancing. We present a set of simulations which allows us to estimate the average loss. For the simulation, we generate draws of interest rates using a process fit to the US interest rate data from 1961 to 2024.[17] We assign households to get a mortgage following the empirical proportions in Figure 1d, 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.[18] We take the size of the mortgage to be given by the amount in figure 1d for that specific income-age

[15] 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. The households that are systematically asleep are more likely to be found among households with very high incentive to refinance, thus generating a decrease in the probability of refinancing, as in the figure.

[16] Model 3 in Table 2 estimates a probability of being asleep but does not have a psychological cost of refinancing as in the full model. We choose this specification as it is easier to match to the US setting as it does not require translating the psychological switching cost from the Danish setting to the American one. In the Appendix we show that a specification designed to match the the model with both psychological factors yields similar findings with a loss magnitude about 20-30 percent lower.

[17] 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 $\tau \approx 1.0173$.

[18] 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.

group. We compute the mortgage payment using a mortgage calculator assuming the average mark-up interest rate (relative to market rates) for that income group.[19]

Once a household has taken on a mortgage, we follow Andersen et al.'s model of mortgage refinancing and assume that refinancing occurs only if a household is "awake". Formally, each household can 'wake up' and check for refinancing opportunities each year with an i.i.d. probability $1 - f_j$, which depends on the income group. When a household wakes up, they refinance if it is the optimal decision to do so. We implement the Agarwal et al. (2013) square-root rule for determining the optimal threshold value of the difference in the current interest rate and interest rate of the mortgage at which it becomes advantageous for households to refinance (see Section D 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 annual 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 being inattentive in mortgage payments over all the years of the mortgage.[20] We then divide this lifetime net loss by the total number of years with a mortgage to compute an annual net loss L_j due to the behavioral friction. 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.

As Table 2 summarizes, we estimate a loss of \$76 for the low-income group and a loss of \$261 for the high-income groups. Although higher income households are less likely to be asleep, they are also more likely to own a home and have larger mortgages, causing them to suffer a higher expected loss in dollar terms.

Validation of the Simulations. We can do a partial validation of the model by comparing how closely we match the evidence in the existing papers. First, using data from the simulation, we reproduce the key figure above from Andersen et al. (2020). We would not expect to perfectly match the patterns given that we are using US as opposed to Danish parameters. Still, as as Figure D3 shows, we fit the patterns reasonably well. The distribution of incentives has a substantial right tail, same as Figure D2. Furthermore, the probability of refinancing in a given quarter is around 8 percent for positive incentives, in the ballpark of the empirical one.[21] The probability does not decline for higher incentives given that our estimates have a limited degree of unobserved heterogeneity modeled. Second, we can check the matching with the estimate of Keys et al. (2016) that, conditional on refinancing being

[19] 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.

[20] 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.

[21] Given that our simulations are run at the annual level, the quarterly probability of refinancing in the figure is rescaled from the annual one.

optimal, households would on median save $184*12=$2,208 per year by refinancing. In our sample, we compute a comparable average median saving of $2,388 per year. Overall, we take these two comparisons to be a validation of the model.

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. Still, as we showed, it comes reasonably close to matching the evidence from Andersen et al. (2020). In the Appendix D 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 of estimated loss are similar qualitatively and 10 to 20 percent lower in magnitude than the benchmark one.[22]

Second, as mentioned above, this set of simulations assumes an i.i.d. friction across the years, as opposed to assuming (as we do for other behavioral frictions) that a fixed fraction of households have a persistent friction. The evidence on this friction from Andersen et al. (2020) speaks directly to the distribution of the friction over time, as opposed to other settings. Third, we make the assumption that households that refinance all 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.

4.2 Suboptimal Credit Card Debt Repayment

Credit card borrowing is very common in the United States as documented for example in Lee and Maxted (2023). For this behavioral friction we focus on the decision of which credit card to repay, among individuals with a credit card balance on at least two credit cards. Figure 1e shows the share of households with at least two credit cards with balance using SCF data, by age and income group. The group with the highest incidence of borrowing on multiple cards tends to be the middle income group, peaking at nearly 40 percent of the population, with the high-income and low-income group at somewhat lower levels. For the share of population at risk s_j we take the average of this fraction over the ages. The plot also reports the average credit card balance for that group, with adjustment factors to compensate for the fact that the extent of credit card borrowing is significantly under-reported in the SCF (Zinman, 2009).[23]

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, the average repayment follows different patterns, with individuals tending to repay equally, or repaying the credit 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

[22] We stick to 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 less obvious.

[23] 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 and by 1.5 in 2016 and 2019.

(as per the calculations of Gathergood et al. (2019)). 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 level of the borrower, the paper shows that the incidence of the behavioral friction is very similar across a number of dimensions, such as the total payment, the interest rate difference, or how long individuals have had a card. We thus assume that the rate with the friction is the same across income groups.

To measure the cost of the friction, we use the calculations in Tables 1 and 2 in Gathergood et al. (2019), which reports 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 balance on the credit cards (since that is a number we observe in the SCF). The extrapolation 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 across the two settings.

For individuals borrowing on 2 credit cards, the mean annual saving (in British pounds) is 65 pounds (Table 2, Panel B), which is 1.5 percent of the average revolving credit card balance over the two cards, which on average is 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. Table 2 summarizes our estimates for s_j, f_j and L_j by income group.

Caveats/To-Do's. An important question is whether the allocation of repayments represents a behavioral friction or some form of optimal decision-making. Several pieces of evidence from both Ponce et al. (2017) and Gathergood et al. (2019) point towards a behavioral friction. For one thing, a survey of credit card borrowers in Ponce et al. (2017) indicates that over 60 percent do not compare the interest rate of cards. Second, the evidence from both papers points to a (suboptimal) balance matching heuristic as the most likely explanation, A caveat to the above calculations is that we are using SCF data on credit card borrowing that 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 have 2 or more credit cards with revolving debt.

4.3 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 minimum payment is the minimum dollar amount that must be paid each month on an outstanding credit card balance. A late fee typically averages $30-$32. We measure the share of individuals in each income group who incurred at least one late fee within the past year, and compute the savings from paying no such fees.

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 (Consumer Financial Protection Bureau, 2024b).[24] Given that survey responses may not correctly report the extent of credit card usage or borrowing, we scale these estimates using administrative data from Consumer Financial Protection Bureau (2021, 2023, 2024a). Consumer Financial Protection Bureau (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, Consumer Financial Protection Bureau (2024a) and Consumer Financial Protection Bureau (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. Figure 1g displays the estimate for s_j and f_j by income group and age.

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 (Consumer Financial Protection Bureau, 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. This number is assumed to be constant across the income groups, given the lack of additional information.[25] Given that the average cardholder pays \$89.91 in late fees per year, and 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 in late fees on average. Table 2 presents our estimates for s_j, f_j, and L_j.

4.4 Paying Overdraft Fees

We define an overdraft fee as a penalty charged by a financial institution for a transaction greater than available funds when the financial institution covers the transaction. We measure the incidence of overdraft fees by income group using the 2023, 2024, and 2025 Consumer Financial Protection Bureau (CFBP) Making Ends Meet surveys Consumer Financial Protection Bureau (2024b), scaled to match the administrative data estimates in Low et al. (2017).

Using the 2023, 2024, and 2025 CFPB Making Ends Meet surveys (Consumer Financial Protection Bureau, 2024b), we compute the share s_j as the share of households with a checking or savings account. As Figure 1f shows, this fraction is over 90 percent for the higher income groups, and 70 percent or higher for the lower income group. The surveys additionally 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 1f 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.[26] As per our survey data,

[24] This dataset only has income and age bins 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.

[25] To the extent that card companies charge interest on late fees, this calculation understates the losses, especially for low-income borrowers who are likely to pay a higher APR.

[26] In the survey data, the number of overdrafts is reported in bins. We take the midpoint of each intermediate bin and, given the heavy concentration of many overdraft fees being paid by a few individuals, 2.5 times the top bin.

conditional on overdrafting at least once, the average person overdrafts 5.793 times in a year.[27] In the administrative data from Low et al. (2017), the corresponding number of average overdrafts is 8.480,[28] so we scale up the number of overdrafts in the survey data (and thus our estimates for L_j) by 8.480/5.793.

Table 2 presents our estimates for s_j, f_j, and L_j. The expected loss from overdraft fees is highest for the low-income group, at \$104, with a loss that is smaller, at \$45, for the high-income group. Other sources are consistent with the key estimate that the losses due to overdraft fees are larger for low-income individuals, e.g., the New York Fed's 2023 Survey of Consumer Expectations (Leonard et al., 2025).

5 Insurance Frictions

5.1 Choosing Dominated Insurance Plans

We define a strictly 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. Such a plan is financially inferior for all enrollees. We measure the prevalence of dominated plans among employers and the share of workers selecting these plans by income group. We focus on the active choice of dominated insurance plans, as opposed to the choice of dominated plans due to changes in plan features and inertia in choice, as in Handel (2013).[29]

First, we estimate the share of individuals within each income group that are offered a health insurance plan which includes a dominated option, since being in this group is a pre-condition to displaying the friction. Since there is no direct data on this, we estimate first the share in each income group that has a health insurance plan through the employer, using data from the Survey of Consumer Finances (SCF).[30] This share is much higher for the high-income group than for the low-income group. We do not have micro level evidence of what share of health insurance coverage includes a dominated plan, so we follow Liu and Sydnor (2022) which documents that 37% of firms in their analysis sample include one strictly dominated plan in the set of options made available to workers.[31] We thus define the share of people subject to a friction s_j as the share in an income group with a health insurance plan through the employer, times 0.37. As the table below shows, this share is steeply increase in the income level.

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. (Liu and Sydnor (2022) provides evidence from a larger set of firms, which is the reason we focus on it for the estimate of the monetary loss below, but does not have evidence on the incidence of dominated choice by employee income.) Figure III Panel A from the paper documents in each \$10,000 salary band the share of employees who

[27] The number of overdrafts is a categorical variable in the 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.

[28] The number of overdrafts is represented categorically in the admin 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, individuals with 11-20 overdrafts as having 15 overdrafts, and individuals with 20+ overdrafts as having 25 overdrafts.

[29] For the latter phenomenon, we are not able to locate evidence on how common it is, and its share across income groups.

[30] We use data from the 2013, 2016, and 2019 waves of the SCF, using the variable `X6347` to measure the proportion of people with employer provided medical insurance in each income group.

[31] Liu and Sydnor (2022) restrict their analysis sample to firms that offer one High-Deductible plan and one Low-Deductible plan.

choose the dominated plan. For our purposes, we aggregate these bands into broader income brackets to construct the Low/Middle/High income groups. Leive et al. (2025) using data from employee choice at a university also document a steep gradient in the choice of dominated insurance relative to income. Rasmussen and Anderson (2021) with data from the administrative data in the Netherlands also documents that the choice friction is more common among lower-income individuals. As far as the average share with the friction, the rate of choosing the dominated plan in Liu and Sydnor (2022)'s context is 53%, which is very similar to the 55% documented in Bhargava et al. (2017).

Finally, we compute the annual loss L_j from the friction. Four possible references are Bhargava et al. (2017) which estimates an average loss of $323 per year, Liu and Sydnor (2022) which estimates $1,121, Leive et al. (2025) which estimates a median loss of $1,700 and Rasmussen and Anderson (2021) which estimates $466 per year. The closer estimate to a representative sample of US consumers is from Liu and Sydnor (2022), which documents the pattern for dozens of US companies, as opposed to Bhargava et al. (2017) which documents choice in 1 company, Leive et al. (2025) which focuses on one university and Rasmussen and Anderson (2021) which estimates choice in the Netherlands.

The final column in the table below presents the average incidence of the friction in each income group, that is, $s_j * f_j * L_j$.

Notes and Caveats. We note that the calculations above make a number of assumptions. A first assumption underlies the computation of dominated insurance plans; for households with borrowing constraints, the high-deductible plans with unforeseen expenditures can present a higher difficulty paying compared to the payment of predictably higher premium for the low-deductible plans (Ericson and Sydnor, 2018). Second, we made assumptions about the share of individuals facing a choice of insurance plans including a dominated plan and monetary loss in case of choice of a dominated plan. When multiple estimates exist, we used the one from Liu and Sydnor (2022) which has evidence from the largest sample of US companies we are aware of. Alternative estimates can be replaced to produce alternative versions of the table above.

5.2 Suboptimally Lapsing Life Insurance

We obtain data on the prevalence of TLIs and their face values from the Survey of Consumer Finances (SCF). The SCF provides cross-sectional data on the ownership of TLI across various ages and income levels. Since the SCF is not a panel data set, we do not have data on TLI purchases. We are also not aware of a panel data set that provides information on term life insurance (and face values). We thus back out the TLI new purchases from the cross-section holdings in the SCF and estimates of lapsing rates as detailed here.

In figure 1i we plot for each SES group (as measured by the cross-sectional income) and 5-year age group the share of individuals with a long-duration TLI, as well as its average face value. We focus on TLI with longer duration since our measures of saving are computed relative to switching to a 10-year TLI. More specifically, to compute the share of individuals with long-duration TLI, we take the share with a reported TLI in a 5-year age group[32] and

[32]The proportion of people who purchase TLI at 25 is equivalent to the average proportion of people who own TLI between 25 and 30, and

deflate it by 0.73, as we estimate that 73% of TLI are for durations of 15 years or longer.[33] We additionally compute the average policy size for a given age-income group as the midpoint between the 25th and 75th percentile policy face values for that group. [34]

The dots show the expected pattern that life insurance holdings peak at the age of 40-50, and are higher for higher income individuals (as in Gropper and Kuhnen (2025)). In addition, the amount of coverage (shown in thousands of dollars) is significantly higher for higher-income individuals.

To impute the TLI purchases from the cross-sectional holdings, as well as the share of people lapsing, we use the rate of lapsing calculated in figure 1B of Gottlieb and Smetters (2021) (attached as figure E1). The lapsing rate is quite substantial especially in the first 2 years of a TLI policy, and especially for policies with lower coverage. As Gottlieb and Smetters (2021) document in their paper, this rate of lapsing is also much higher than the anticipated rate of lapsing from a survey of consumers with life insurance policies.

As Figure E2 illustrates, we use the cross-sectional holding of TLI at an age and the lapsing rate to back out the rate of new purchases of TLI at different ages, as follows. Starting from the cohort at age 25, we apply the rate of lapsing from figure E1 to the age-25 cohort, with the red dots indicating the residual members of that cohort with an active TLI.[35] 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.[36]

With this information, we can compute the prevalence of the life insurance friction. Specifically, we consider suboptimal lapsing to be the individuals who lapse within the first 10 years of their policy (i.e., those who lapse between the blue and yellow dots in figure E2). These individuals could have purchased a 10-year policy instead, saving on their premiums. Going back to our earlier parameters, s_j corresponds to the proportion of people who purchase 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. Compulife (2013) provides us with both the 10-year and 20-year TLI premiums across several different insurance providers.[37] Figure E3 gives a few examples of 10-year vs 20-year TLI premiums across

similarly for later age groups.

[33] 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.

[34] 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 determining the policy face value.

[35] For the first 5 years after purchase, we use figure E1B 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 E1A.

[36] 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.

[37] We assume individuals have regular health, are non-smokers, and purchased a 20-year TLI in California, October 2019.

various ages and policy sizes. The figure shows 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). We use the medians (i.e., black dots) to determine the annual saving available from switching for each income-group and 5-year age interval.

To determine the annual loss L_j for lapsers, we estimate the average of the 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 E2a), 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) as \$10.75, as displayed in Table E1. We distribute the savings evenly annually among the 5.1% of low-income individuals who lapse. We similarly compute savings for the later age groups.

Table E1 shows s_j, f_j, and L_j for each income-group and 5-year age interval. In the model, the share with a friction is constant over age, so we set f_j equal to the average f_j across the ages for each income group. We let s_j and L_j vary for different ages. Table 2 represents our summary of the life insurance lapsing friction.[38] The share with a friction is sizable and somewhat larger with low-income individuals, at 0.178, as opposed to 0.157 for higher-income individuals. The share with a life insurance is much higher for high-income individuals, as we commented and as in Gropper and Kuhnen (2025). The loss is also quite a bit higher for higher-income individuals because they purchase higher coverage life insurance.

Notes and Caveats. We note that the calculations above make a number of assumptions to compute the key statistics about TLI lapsing. Some key assumptions relate to (i) how we infer the take up rate of long-duration TLI, (ii) the assumption about the share lapsing due to a friction, and (iii) how we compute the loss due to the friction. Regarding (iii), we measure the loss of lapsing as the savings associated with taking a shorter-duration life insurance contract. We could alternatively have measured the losses as the benefit of reselling the life insurance on the secondary market. This alternative computation likely would yield larger estimates of losses but we did not pursue this route because the secondary market for TLI is very thin. We acknowledge regarding (ii) 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 E1B. The evidence from Ellis and Jaspersen (2025) on lapsing rates by quantiles of wealth suggests that our measure understates the extent to which lapsing rates are higher for low-income consumers.

[38] Table 2 averages over all ages (22-90), resulting in a overall s_j that is lower than the ones presented in Figure 1i.

6 Benefits Frictions

6.1 Not Claiming EITC Benefits

Figure F1 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 can estimate the share of people that are eligible (s_j in the model) 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 in the model). We document this as function of the (permanent) income group which we determine using the panel nature of the PSID. Table 2 (restricted to ages 22-65) shows that in the PSID data, the low income group has an average eligibility of 0.565 for an average payment of 1,272. For the middle-income and low-income group the eligibility numbers are much smaller; the numbers are non-zero in the high-income group because the income group is determined as permanent income, and income shocks can land a high-income household to lower income levels. As far as the share f_j with a friction, in 2020, the EITC claiming rate was approximately 80% (Coleman et al., 2024; Bhargava and Manoli, 2015), implying a behavioral friction of $f_j = 0.2$.

Table F2 reconstructs Table 2 using the data from our model (again restricting to 22-65). As one would expect, the proportion not claiming (f_j) is identical across both tables. 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 average loss due to not claiming (L_j) is sizably lower in our model. The overall expected loss ($s_j * f_j * L_j$) is about 20 percent larger in the model simulations compared to the empirical estimates, for the low- and middle-income groups. The model overstates the losses for the high-income group by an order of magnitude, but the estimated loss is still small compared to the other frictions.

Notes and Caveats. As mentioned above, 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 across households. A second caveat is that we assume that non-claiming households do not claim no matter what the amount of EITC eligible; there is some evidence that the amount of non-claiming is higher for lower benefit levels, which we do not model (Coleman et al., 2024; Bhargava and Manoli, 2015). Third, we assume that 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).

6.2 Not Claiming SNAP Benefits

We model SNAP eligibility using data from the 2011-2019 waves of the PSID, applying the SNAP rules summarized in Appendix F.[39] We estimate the share of people that are eligible for SNAP (s_j in the model) 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 in the model). We document this as function of the (permanent) income group which we determine using the panel

[39] 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.

nature of the PSID. Table 2 shows that in the PSID data, the low income group has an average eligibility of 0.689 for an average payment of 2,798. For the middle-income and low-income group the eligibility numbers are much smaller. For the share f_j with the friction, we model SNAP claiming rate as being 82% following Vigil (2022).

Table F3 reconstructs Table 2 using the data from our model. As one would expect, the proportion not claiming (f_j) is identical across both tables. 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 (Finkelstein and Notowidigdo, 2019).[40]

6.3 Combining EITC and SNAP

In the life-cycle simulations, for computational reasons we assume that the 20 percent of individuals that do not claim the EITC even when eligible ($f_j = 0.2$) are also the ones that do not claim SNAP when eligible. We acknowledge that in the data a perfect correlation between the two frictions is unlikely. We view it as a simplifying assumption which lowers the computation burden (as the two frictions are modeled as one). We also note that we are not aware of any micro-data evidence on what the correlation in not-claiming may be across the two frictions.

7 Health Frictions

7.1 Not Taking Statin Medications

Nearly two thirds of the US population have at least one risk factor for cardiovascular disease (Fryar et al., 2024), based on blood pressure, lipids, glucose, and BMI. Indeed, deaths due to cardiovascular disease are a large fraction of all deaths, especially at older ages, as figure G1 shows using CDC data.

For the group at risk, one category of medications, statins, have been proven to be highly effective in mitigating the risk of cardiovascular disease, as we summarize below. Indeed, statins are recommended for 40-50 percent of the US population of ages 40-75. Yet, the take up of statins in this group is far from 100 percent. We summarize below evidence on the share of risk s_j, the fraction f_j that does not take statins, and its associated loss L_j in terms of cardiovascular disease and mortality.

First, we document for each income and age group the share of individuals who meet guidelines for statin use, our measure of s_j. We measure this using data from the 2010-19 NHIS, where the `cholhighyr` variable asks

[40] Finkelstein and Notowidigdo (2019) run 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 under any treatment condition is needier, implying that the group that does not claim even with the nudge has higher need. The combination of findings suggests that who claims and does not claim may well depend on setting and intervention.

respondents if they have had high cholesterol within the past 12 months. Figure 1j shows that this share increases with age up to 60 percent at age 70 and is quite similar across the income groups.

Next, we use the Verma et al. (2017) measure of those who should take statins but fail to do so. The paper calculates this share using NHANES data from 2005-2012, and we use their income-quartile level estimates from table 3 of the paper. We plot this share also in Figure 1j. 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 of failing to take statins, we summarize the results of over a half dozen RCTs on the effectiveness of statins. Most of these studies were run in the 1990s and contributed to establish the effectiveness of statins. The typical study randomizes individuals into a statin arm or a placebo arm. The design is necessarily 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 these other medications. Most of the studies focus as primary outcome on the occurrence of a major cardiovascular event (such as a heart attack), with mortality due to cardiovascular events as a secondary outcome (due to lower statistical power). Some of the studies report the first stage, that is, the extra share that take the statin in the treatment group, compared to the control group. In this case, we compute the treatment-on-the-treated estimate, rescaling the ITT estimate by the first stage.[41]

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. If there is no estimate of the first-stage, we report the TOT estimate as equal to the ITT. In the final row, we report the average equal-weighted estimate.

Using the average of Column 4 we assume that failing to take statins increases the cardiovascular mortality by 24.5 percent. Using, the evidence in Figure G1, we compute the impact on overall mortality at different ages, Table 2 summarizes the overall impact of failing to take statins.

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

7.2 Not Screening for Colon Cancer

Among the causes for preventable deaths, colorectal cancer (CRC) is first-order. As figure G2 shows, CRC deaths are about 3 percent of deaths among 50-59 year olds and about 1 percent of deaths among older people. We sum-

[41] 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 $1/(87-12)$.

marize below evidence from RCTs indicating that screening can reduce significantly the mortality from CRC. We then estimate from NHIS data what share of low-income, middle-income and high-income individuals undertake regular screenings. We assume that those that do not screen are subject to a higher mortality rate, as per our calculations.

We do the calculations for CRC deaths given that it is one of the areas among health behaviors in which there is clearer RCT-based evidence on mortality impacts of screening. We envision this as an example of how regular health screening can impact life-cycle outcomes and inequality, not as in any way a complete picture of the impact of preventative health.

Our summary of the evidence on CRC prevention is as follows. The original evidence for CRC screening comes from an RCT (Mandel et al., 1993) with 46,000 participants showing a (statistically significant) 33 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 (precisely estimated) reduction in the CRC-specific mortality of 28 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.

Overall, we also assume that skipping the lower-nuisance screening (the fecal testing or the sigmoidoscopy) is a behavioral friction. Putting the most weight on the second study, yielding the most precise estimate, we assume that CRC screening can reduce CRC mortality by 28 percent, 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 order to measure the share with a behavioral friction, we use the NHIS and measure the share f_j in each income group aged above 50 that has not undertaken a CRC screening in the last 5 years. As Table 2 shows, this share is 62 percent for the low-income group and is 44 percent for the high-income group. The share at risk s_j is the share of that group that is 50 years or older, since all individuals above 50 are recommended the screening.

Notes and Caveats. An assumption of the analysis is that skipping the CRC screening is a behavioral friction. Given that colonoscopies are a significant nuisance (typically a day or fasting and a day-long bowel prep), this is not an obvious assumption. However, fecal testing and sigmoidoscopies are significantly lower cost and lower annoyance. Another caveat is that the estimates for the impact of this friction are conservative because they do not include any economic impact of the higher incidence of colorectal cancer, such aslower labor force participation, losses in earnings and disability.

7.3 Smoking

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. We start by plotting in Figure B1 the share of smokers as a function of age for the three income groups. The share is significantly higher for the low-income group, reaching above 30 percent, peaking around age 50 for this group; it peaks in the early 20s and 30s-40s for the high- and middle-income groups, respectively, and at significantly lower levels. A relevant parameter is the share of smokers that intend to quit, which we consider to be the relevant population at risk, since we deem individuals who are not aiming to quit time-consistent smokers. Figure B2 shows that the share aiming to quit is about constant across the groups, and across most ages, at about 70 percent.

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 a such measure, there are two main difficulties. First, continuing to smoke versus quitting has different health implications whether one stops at say age 25 versus stops smoking at age 60; the cumulative damage due to smoking is much more serious in the latter case and thus the benefits of stopping are smaller. Second, it is common for smokers to quit and then re-start; we thus need to set a threshold for quitting smoking for a long enough period.

On the first issue, we use NHIS mortality data to estimate the difference in mortality rate 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. Figure B3 compares the mortality of former and never smokers to the mortality of current smokers. As is well known, the mortality rate of non-smokers is much lower than the one of smokers, on average 1/3. Interestingly, former smokers who quit by age 50 have a quite similar mortality rate as non-smokers. In contrast, the mortality rate for former smokers who quit after age 50 is closer to the mortality of smokers.

Based on this evidence, we designate age 50 as a critical age for quitting. We compute for each of the three income groups the incidence of the behavioral friction as follows. 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, as it indicates a behavioral friction.

We measure the loss due to smoking L_j by comparing the mortality of continuing smokers past age 50 (including those who never quit) to the mortality of smokers who quit before age 50 (including those who never smoke). Using the evidence above in Figure B3, we estimate that failing to quit increases the mortality by a factor of 2.36 for age 50-74 and by a smaller factor of 1.90 for ages 75+.[42] (It is reasonable that the latter factor is smaller given that

[42] These factors are the weighted average of the income group-specific factors in Table B1, weighted by their sample shares. The factors estimated from the sample pooled across income groups are 2.92 and 1.90 for ages 50-74 and 75+, respectively. These factors are higher due to compositional effects, whereby low-income individuals are concentrated in the late-quitting group.

mortality in levels is much higher at older ages, which moderates the extent to which smoking can increase it, as a proportional factor.) The mortality impact of smoking is similar to the impacts estimated in prior studies (Doll et al., 2004; Pirie et al., 2013; Jha, 2020). It amounts to a shorter life expectancy at 50 by 6.7 years.[43]

Table B1 summarizes the findings above. The share at risk s_j is the share that is current smokers as of age 50 who want to quit, or 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 coded in terms of mortality loss.

Caveats. Our interpretation of smoking as a behavioral friction depends on a self-control interpretation: an individual would like future selves to stop smoking, but does not want to do so at present. The present bias interpretation motivates our focus exclusively on smokers that aim to quit. Observational evidence from Gruber and Köszegi (2001) and evidence on demand for a commitment device for stopping smoking in Giné et al. (2010) suggest this interpretation is plausible. An alternative interpretation is of smoking as rational addiction (Becker and Murphy, 1988). Under this alternative interpretation, one can still take the estimates from our simulations, but they do not represent a behavioral friction but rather an optimizing ex ante choice. A different caveat is that the simulation incorporates exclusively the mortality costs, leaving out the loss of employment due to disability or other utility costs. The calculations also do not include the (significant) annual cost of purchasing cigarettes. On the other side of the equation, we do not account for the hedonic benefits of smoking.

8 Aggregating Across Frictions: Empirical Evidence

We aimed to summarize the impact of each friction with the key summary statistics s_j, f_j, and L_j. In particular, the product $s_j * f_j * L_j$ is an estimate of the average per-person impact of the behavioral friction on post-tax spendable income for that income group. In this section, we thus compare the estimate for $s_j * f_j * L_j$ across the behavioral frictions. We do this comparison both in levels in dollars, and as a percent of the average annual income for that group.

Before we present the relevant figures, we want to stress a number of caveats that come with the estimates. First, the estimates reflect a combination of various data sources, including coding of survey responses, findings from the literature, and model simulations. There is uncertainty in each of those estimates and subjective decisions which influence the estimate. We are well aware of this and want to be clear that we see this as an attempt to present a framework with the goal to making comparisons, but recognizing that the actual magnitude reflects a number of assumptions. Second, the estimates collate into one variable different types of losses – in some cases the losses are through foregone employer match, in other cases they reflect increased spending, in other cases still increased mortality. While we aim to compare across, it is important to keep in mind such differences. Third, while we are interpreting the losses as due to behavioral frictions, one may view some of them as optimizing choices, e.g.,

[43] This estimated reduction of life expectancy 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 7.9 years.

smoking; under this alternative interpretation, it is still possible to interpret the findings as the estimate of a cost which is compensated by some net benefit in the view of the individual.

Figure 2 presents for each friction the expected loss for the low-income group (x axis) and for the high-income group (y axis). Panel A reports losses in dollars, while Panel B reports losses as percent of the annual average (post-tax) individual income.

In dollar terms, there are frictions that clearly affect more low-income earners – not claiming benefits – and other frictions that affect more the high earners – high mutual fund fees. When we consider the losses as percent of income, though, the losses on average loom larger for low-income earners, with all but 2 frictions affecting low-earners more. In addition, 9 frictions affect the average income of low-earners by at least 0.4% of their annual income. Instead, only 2 frictions affect the high-income group by more than 0.4% of income (under-diversification and high mutual fund fees).

While we stress the important caveats above, one can add across the various frictions for an estimated overall impact as percent of the annual income. Doing that, we estimate an impact of 9.3% for the low-income group versus 2.6% for the high-income group.

As a first way to assess the magnitude of these losses, we compare the loss estimate associated with the behavioral frictions against the earnings impact of two government reforms: all states implementing an EITC equal to 25% of the federal EITC, and the government reverting the 2020 tax code to the 2016 tax code (thus reverting the Tax Cuts and Jobs Act of 2017).

Regarding the first reform, in 2025, 20 states offered an EITC supplement equivalent to a set percentage of the federal EITC level, with the median supplement equal to 22.5% of the federal EITC and the mean supplement equal to 25.8%. We assume a hypothetical policy change where all states offer an EITC supplement equivalent to 25% of the federal EITC, and calculate how that would change the impact on the expected losses of the lower- and higher-income groups. For simplicity, we assume that this additional EITC supplement would not change the likelihood of EITC claiming (i.e., f_j), although it is likely that increasing the amount of EITC available may increase its salience to households. Since the high-income group are largely not eligible for the EITC, the additional EITC supplement would only impact the low-income group, who would expect to gain 1.32% on average. The impact of this major anti-poverty policy is only about twice as large as the impact of an average behavioral friction for low-income consumers.

The other government reform we consider is a reversion to the 2016 tax code. The Tax Cuts and Jobs Act of 2017 reduced taxes owed across the income distribution, 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 revert this change, modeling the potential lowered tax burdens as 'losses'. Per Figure 2, the tax schedule reversion would have a major impact on the high-income group, who would expect to lose 2.60% of their post-tax income, relative to the low-income group losing 1.46% of their post-tax income. This tax reform has a larger impact on the high-earners income than the sum of all behavioral frictions combined.

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 is seven times larger than the impact of the EITC reform. In contrast, the losses to high-income consumers from the sum of the behavioral frictions is smaller than the gain associated with one major tax reform.

9 Life Cycle Model

This section describes our life cycle model. 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 jth 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. 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 also assume that all frictions are uncorrelated across individuals; we plan to relax this assumption in future versions.

9.1 Model Description

Demographics. Time is discrete and indexed by $t \in \{t_0, T\}$, where the length of the period is one year. Age is indexed by a_{it} and evolves according to:

$$a_{it} = a_{it-1} + 1. \tag{6}$$

Individuals are born at time t_0 with $a_{it_0} = 0$. 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:

$$D_{it} = \begin{cases} 0 & \text{with probability } \mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i) \\ 1 & \text{with probability } 1 - \mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i) \end{cases} \tag{7}$$

where $\mathscr{D}(a_{it}, \delta_i, \mathbf{f}_i)$ denotes the probability of survival to the next period conditional on an individual's current age a_{it}, permanent income group δ_i, and friction vector $\mathbf{f}_i$.

Each individual has a number of children equal to $\text{kids}(a_{it}, e_i)$, which is modeled as a deterministic function of age and education. The number of children is not required to be an integer. The effective family size is:

$$n_{it} = (1 + \alpha_k \times \text{kids}(a_{it}, e_i))^{\alpha_n} \tag{8}$$

where α_k is the child weight and α_n is the equivalence scale exponent.

Education levels. At the beginning of life, individuals are assigned to one of N_e education groups, $e_i \in \{1, \ldots, N_e\}$. Education determines the deterministic component of income, student debt obligations, the initial distribution of liquid assets, the distribution of children, and the income process parameters. The assignment to education groups depends on friction status.

Income process. Our model of the income process follows Braxton et al. (2025). The process for individual income, y_{it}, depends on whether individuals are employed ($\zeta_{it} = E$) or unemployed ($\zeta_{it} = U$):

$$y_{it} = \begin{cases} \max\left\{\exp\left(\overline{y}(\delta_i, e_i) + f(a_{it}, e_i, \delta_i) + z_{it} + \epsilon_{it}\right), \underline{y}\right\} & \text{if } a_{it} < a_R \text{ and } \zeta_{it} = E \\ \max\left\{\ell \cdot \exp\left(\overline{y}(\delta_i, e_i) + f(a_{it}, e_i, \delta_i) + z_{it}\right), \underline{y}\right\} & \text{if } a_{it} < a_R \text{ and } \zeta_{it} = U \\ 0 & \text{if } a_{it} \geq a_R \end{cases} \tag{9}$$

The first component, $\overline{y}(\delta_i, e_i)$, is an intercept that varies by permanent income group and education. The second component, $f(a_{it}, e_i, \delta_i)$, is a deterministic age profile that is a cubic polynomial in age whose coefficients depend on education and income group. When individuals are unemployed, their wage is a fraction ℓ of their deterministic and persistent income, without a transitory shock. We also impose an income floor of $\underline{y}$.

When individuals are employed, they receive temporary income shocks ϵ_{it} that are drawn from an education- and age-specific distribution. Specifically, ϵ_{it} is discretized from a mean-zero normal distribution with standard deviation $R_E(a_{it}, e_i)$ that varies over the life cycle and across education groups. When unemployed, no transitory shock is received and the mid-point of the discretized distribution is used.

An individual's employment status transitions according to:

$$\zeta_{it+1} = \begin{cases} E & \text{with probability } 1 - p_U(z_{it}, \zeta_{it}; e_i, \mathbf{f}_i) \\ U & \text{with probability } p_U(z_{it}, \zeta_{it}; e_i, \mathbf{f}_i) \end{cases} \tag{10}$$

with initial condition $\zeta_{i0} = E$. The probability of unemployment $p_U(\cdot)$ is a quadratic function of z_{it} whose coefficients depend on whether the individual is currently employed or unemployed and on education group. Certain frictions can increase the unemployment probability.

The persistent component of income evolves according to:

$$z_{it} = \begin{cases} z_{i0} & \text{if } a_{it} = 0, \quad z_{i0} \sim N(0, Q_0(e_i)^2) \\ \rho_z(e_i) \cdot z_{it-1} + \eta_{it} & \text{if } 0 < a_{it} < a_R \\ z_{it-1} & \text{if } a_{it} \geq a_R \end{cases} \tag{11}$$

where persistent income is frozen at its last working-life value upon entering retirement. The innovation has a state-dependent distribution:

$$\eta_{it} \sim N\left(B(\zeta_{it}; e_i),\, Q(\zeta_{it}; a_{it}, e_i)^2\right) \tag{12}$$

Permanent income groups. We assume that there are $N_\delta = 3$ permanent income groups, $\{\delta_j\}_{j=1}^{N_\delta}$. The permanent income group affects many things in the model, including an individual's deterministic age profile, survival probabilities, 401(k) access, and the prevalence of frictions.

Liquid account. Individuals have access to a liquid account that can be accessed costlessly. The balance in this account at the beginning of time t is denoted by L_{it}, and has the following law of motion:

$$L_{it} = \begin{cases} L_{i0} \sim F_L(\cdot \mid e_i, \mathbf{f}_i) & \text{if } a_{it} = 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i)) \left(R^f + \tau^0_L\right) & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) < 0 \\ (S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i)) \cdot R^\theta_{it} & \text{if } S^L_{it-1} - \mathscr{L}_{it-1}(\mathbf{f}_i) \geq 0 \end{cases} \tag{13}$$

where $F_L(\cdot \mid e_i, \mathbf{f}_i)$ is the distribution of initial liquid assets, which depends on education group and friction status. S^L_{it} is an individual's liquid savings choice at time t, subject to a borrowing limit:

$$S^L_{it} \geq -\underline{L}(a_{it}, e_i, \delta_i) \tag{14}$$

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. R^θ_{it} is the portfolio return described below. R^f is the constant gross risk-free rate. τ^0_L is the interest rate spread on borrowing, so individuals borrow at $R^f + \tau^0_L$. The term $\mathscr{L}_{it}(\mathbf{f}_i)$ denotes the total dollar loss from frictions, described below.

When $S^L_{it} - \mathscr{L}_{it}(\mathbf{f}_i) > 0$ and the individual is saving, the individual earns an after-tax return that depends on a blended capital gains tax rate. This tax rate is computed as a function of adjusted gross income (AGI), which combines taxable labor income and net capital gains. Specifically, 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 then:

$$\tau_{\text{cap}}(\text{AGI}) = \tau_{\text{reg}}(\text{AGI}) \cdot (1 - \omega_{\text{pref}}(\text{AGI})) + \tau_{\text{pref}}(\text{AGI}) \cdot \omega_{\text{pref}}(\text{AGI}) \tag{15}$$

and the after-tax rate of return in the liquid account 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.

Illiquid account. A subset of individuals have access to an illiquid account modeled after a 401(k). Access to this account, $I^X_i(\delta_i, \mathbf{f}_i) \in \{0, 1\}$, depends on an individual's permanent income group and friction status, and is fixed throughout an individual's life.

Contributions to this account, denoted by S^X_{it}, can only be made when individuals are employed ($\zeta_{it} = E$), are employer-matched at a rate m_x up to a cap of c_x as a fraction of income, and cannot exceed a limit $\overline{x}(a_{it})$. Withdrawals are allowed freely in retirement but are subject to a penalty rate $\phi_x(a_{it})$ prior to a threshold age.

When job loss occurs ($\zeta_{it} = U$), remaining balances are multiplied by a vesting rate $\mathcal{V}(a_{it}, y_{it}) \in (0,1)$:

$$\mathcal{V}(a_{it}, y_{it}) = 1 - p_{\text{vest}}(a_{it}, y_{it}) \times v_{\text{cond}} \tag{16}$$

where $p_{\text{vest}}(a_{it}, y_{it})$ is the probability of a vesting-related separation and v_{cond} is the fraction of the balance lost conditional on such a separation.

Given these assumptions, the balance in this account at the beginning of time t, denoted by X_{it}, has the following law of motion:

$$X_{it} = \begin{cases} 0 & \text{if } a_{it} = 0 \\ R^{\theta}_{it}\left(X_{it-1} + S^{X}_{it-1}\right) & \text{if } a_{it} \geq a_R \\ R^{\theta}_{it}\left(X_{it-1} + S^{X}_{it-1} \cdot (1 + \phi_x(a_{it}))\right) & \text{if } \zeta_{it} = E \text{ and } S^{X}_{it-1} < 0 \\ R^{\theta}_{it}\left(X_{it-1} + S^{X}_{it-1} + y_{it-1} \cdot m_x \cdot \min\left\{\frac{S^{X}_{it-1}}{y_{it-1}},\, c_x\right\}\right) & \text{if } \zeta_{it} = E \text{ and } S^{X}_{it-1} \geq 0 \\ R^{\theta}_{it}\left(X_{it-1} \cdot \mathcal{V}(a_{it}, y_{it}) + S^{X}_{it-1} \cdot (1 + \phi_x(a_{it}))\right) & \text{if } \zeta_{it} = U \end{cases} \tag{17}$$

Total contributions in the employed-positive case are capped at $\overline{x}_{\text{total}}(a_{it})$. The return on assets in this account is the same portfolio return R^{θ}_{it} as in the liquid account. Individuals face the following constraints on their contributions:

$$S^{X}_{it} \in \begin{cases} \{0\} & \text{if } I^{X}_{i} = 0 \\ [-X_{it},\, 0] & \text{if } a_{it} \geq a_R \\ \left[-\frac{X_{it}}{1+\phi_x(a_{it})},\, \overline{x}(a_{it})\right] & \text{if } \zeta_{it} = E \\ \left[-\frac{X_{it} \cdot \mathcal{V}(a_{it}, y_{it})}{1+\phi_x(a_{it})},\, 0\right] & \text{if } \zeta_{it} = U \end{cases} \tag{18}$$

Portfolio choice. There are two assets in which individuals can invest their positive financial wealth. The first is a one-period risk-free bond that delivers a constant gross return R^f. The second is a risky stock with return:

$$R^{s}_{t+1} = R^f \cdot \exp\left(\mu_s + \epsilon^{s}_{t+1}\right), \quad \epsilon^{s}_{t+1} \sim N(0, \sigma^2_{rs}) \tag{19}$$

where μ_s is the equity premium and σ_{rs} is the volatility of stock returns. Stock returns are idiosyncratic.

Individuals make one portfolio choice, $\theta_{it} \in [0,1]$, that determines the share of their positive assets in both the liquid and illiquid accounts allocated to the risky stock. Participation in the stock market incurs a per-period monetary cost, $\tau_p(\delta_i)$, that reduces consumption whenever the individual saves positively and allocates a positive share to stocks. Certain frictions restrict the portfolio choice; details are provided in Section 9.2. Given θ_{it}, an individual's portfolio return is:

$$R^{\theta}_{it} = R^f + \theta_{it-1}\left(R^{s}_{t} - R^f\right) \tag{20}$$

Wealth. At time t, total wealth is:

$$W_{it} = L_{it} + I_i^X \cdot X_{it}. \tag{21}$$

Social security benefits. In retirement, individuals receive deterministic social security benefits. We approximate individual i's average indexed yearly earnings at retirement as:

$$\widehat{\text{AIYE}}_i = \text{AE}(e_i, \delta_i, z_{it:a_{it}=a_R-1}) \tag{22}$$

where $z_{it:a_{it}=a_R-1}$ is the individual's persistent income in their final year of working life and $\text{AE}(\cdot)$ is a function that approximates true average lifetime earnings. Social security benefits are a piecewise linear function of $\widehat{\text{AIYE}}_i$, following the formula used in Catherine (2022):

$$T_{it}^{ss} = \mathcal{T}_{ss}(\widehat{\text{AIYE}}_i) \cdot \mathbf{1}_{a_{it} \geq a_R} \tag{23}$$

EITC. During working life, individuals receive Earned Income Tax Credit benefits that depend on age and taxable income:

$$T_{it}^{\text{eitc}} = \widehat{\text{EITC}}(a_{it}, y_{it}^T) \tag{24}$$

where $\widehat{\text{EITC}}(\cdot)$ is a polynomial approximation of the federal EITC formula whose coefficients and income cutoffs vary by age group. EITC payments are not taxable.

SNAP. In all periods, individuals receive Supplemental Nutrition Assistance Program (SNAP) benefits:

$$T_{it}^{\text{snap}} = \widehat{\text{SNAP}}(a_{it}, y_{it}^{\text{gross}}) \tag{25}$$

where y_{it}^{gross} is gross income (labor income during working life, social security benefits during retirement) and $\widehat{\text{SNAP}}(\cdot)$ is a polynomial approximation of the federal SNAP formula whose coefficients and income cutoffs vary by age group.

SSI. In retirement, individuals have access to the Supplemental Security Income (SSI) program, following a simplified version of Catherine (2022):

$$T_{it}^{\text{ssi}} = \begin{cases} \max\{\overline{y}_{\text{ssi}} - T_{it}^{ss}, 0\} & \text{if } a_{it} \geq a_R \text{ and } W_{it} < \overline{W}_{\text{ssi}} \\ 0 & \text{otherwise} \end{cases} \tag{26}$$

where $\overline{y}_{\text{ssi}}$ is the SSI benefit cap and $\overline{W}_{\text{ssi}}$ is the asset test threshold.

Inheritances. Individuals receive inheritances that are a deterministic function of age and education:

$$T_{it}^{I} = \max\left\{\text{poly}_3(a_{it}; e_i),\, 0\right\} \tag{27}$$

where $\text{poly}_3(\cdot)$ denotes a cubic polynomial in age whose coefficients depend on education group.

Student debt. Individuals repay student debt over the first T_d years of life according to a fixed repayment schedule:

$$T_{it}^{sd} = \begin{cases} \min\left\{\frac{D(e_i,\mathbf{f}_i)\cdot(r_d-1)}{1-r_d^{-T_d}},\; y_{it}\right\} & \text{if } a_{it} < T_d \\ 0 & \text{otherwise} \end{cases} \tag{28}$$

where $r_d = R^f + \Delta_d$ is the student debt interest rate, $D(e_i, \mathbf{f}_i)$ is the debt principal which depends on education group and friction status, and T_d is the repayment horizon. Payments are forgiven in any period where they would exceed labor income.

Income taxation. Taxable income is defined as:

$$y_{it}^{T} = \begin{cases} T_{it}^{ss} - S_{it}^{X} & \text{if } a_{it} \geq a_R \\ \max\left\{y_{it} - S_{it}^{X},\, 0\right\} & \text{if } a_{it} < a_R \end{cases} \tag{29}$$

where 401(k) contributions (S_{it}^{X}) are tax-deductible. Individuals' income tax payments are then calculated according to a progressive income tax schedule:

$$T_{it}^{y} = \mathscr{T}_y\left(y_{it}^{T}\right) \tag{30}$$

Consumption floor and total transfers. The government ensures a consumption floor $\underline{c}$. If an individual's resources after all transfers would be insufficient to consume $\underline{c}$ while respecting the borrowing limit, the government provides a transfer, T_{it}^{floor} to close the gap. Total transfers that individuals receive from the government and in the form of inheritances as T_{it}, where:

$$T_{it} = T_{it}^{\text{eitc}} + T_{it}^{\text{snap}} + T_{it}^{\text{ssi}} - T_{it}^{y} + T_{it}^{ss} + T_{it}^{I} - T_{it}^{sd} + T_{it}^{\text{floor}}. \tag{31}$$

Preferences. Individuals have time-separable expected utility preferences with discount factor β and flow utility:

$$U(c_{it}, a_{it}) = \frac{n_{it}}{1-\gamma}\left(\frac{c_{it}}{n_{it}}\right)^{1-\gamma} \tag{32}$$

where γ is the coefficient of relative risk aversion, c_{it} is consumption, and n_{it} is the equivalence scale. When an individual saves positively and allocates a positive share to stocks, consumption is reduced by the stock market participation cost $\tau_p(\delta_i)$.

Bequests. When individuals die, they receive utility from bequeathing their wealth. The bequest utility follows De Nardi et al. (2010):

$$U_B(W_{it}) = \frac{n_{it} \cdot \psi_1}{1-\gamma} \left(\frac{b_{it}}{n_{it}} \right)^{1-\gamma} \tag{33}$$

where ψ_1 controls the strength of the bequest motive and b_{it} is the bequeathable amount:

$$b_{it} = \psi_2 + W_{it} - \left[\mathcal{T}_y(y_{\text{heir}} + X_{it}) - \mathcal{T}_y(y_{\text{heir}}) \right] \cdot \mathbf{1}_{I_i^X = 1} \tag{34}$$

where ψ_2 controls the non-homotheticity of bequests and y_{heir} is the income of the heir for the purpose of computing the tax on inherited 401(k) balances. The bequest motive uses the same coefficient of relative risk aversion γ as the flow utility.

Summary of problem in working life. Individuals face a dynamic optimization problem with the following state variables: a_{it} (age), e_i (education), δ_i (permanent income group), ζ_{it} (employment status), z_{it} (persistent income), ϵ_{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 θ_{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), ζ_{it+1} (employment status), η_{it+1} (persistent income innovation), ϵ_{it+1} (transitory income shock), and ϵ_{t+1}^s (stock return innovation). The recursive formulation of this problem is presented in Section H.1.

Summary of problem in retirement. In retirement, the income process states z_{it} and ζ_{it} are no longer stochastic (persistent income is frozen and employment is irrelevant). Individuals make the same choices. The relevant sources of uncertainty are mortality and stock return innovations.

9.2 Frictions that Have Been Incorporated

College Attendance (f_i^1). Individuals with $e_i = 1$ who do not have this friction ($f_i^1 = 0$) are treated as having "attended college": they receive a log earnings gain g_c added to the age profile and take on additional student debt D_c. They also pay an upfront cost of \$6,000, designed to capture foregone earnings while attending college, which is split between a reduction in initial liquid assets and a reduction in first-period consumption using a marginal propensity to consume of 0.4, a standard value in heterogeneous-agent macro models (Kaplan and Violante, 2022). The share at risk s is the share of individuals without a college degree, and f is calibrated from estimates of the impact of interventions on college attendance; see Table 2 for the values by income group.

2-Year For-Profit Attendance (f_i^2). When on, a fraction of individuals in the education group $e_i = 2$ are assigned to $e_i = 3$, which has three effects. First, it imposes a log earnings penalty of 11.3 log points that reduces income.

Second, it increases the probability of unemployment by an additive uplift of 1.5 percentage points per year. Third, it increases student debt by approximately $5,100 relative to non-for-profit some-college individuals. These magnitudes are calibrated from the estimates of Cellini and Turner (2019); see Table 2 for the prevalence estimates s and f by income group.

Stock Market Participation (f_i^3). 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; see Table 2 for the values by income group.

Overdraft Fees (f_i^4). This friction imposes a direct dollar loss $\ell_4(a_{it}, \delta_i)$ that is subtracted from the liquid account each period, representing the cost of incurring overdraft fees. The dollar loss varies by age and permanent income group, calibrated from CFPB survey and administrative data; see Table 2 for the prevalence and loss estimates by income group.

Credit Card Late Fees (f_i^5). This friction imposes a direct dollar loss $\ell_5(a_{it}, \delta_i)$ that is subtracted from the liquid account each period, representing the cost of paying credit card late fees. The dollar loss varies by age and permanent income group, calibrated from CFPB survey and administrative data; see Table 2 for the prevalence and loss estimates by income group.

Dominated Insurance Choice (f_i^6). This friction imposes a direct dollar loss $\ell_6(a_{it}, \delta_i)$ that is subtracted from the liquid account each period, representing the excess cost of holding a dominated insurance plan. The dollar loss varies by age and permanent income group, calibrated from Liu and Sydnor (2022) and Bhargava et al. (2017); see Table 2 for the prevalence and loss estimates by income group. Because the model does not explicitly model the health insurance decision, the loss is assigned as an average over the population of individuals with the friction without distinguishing who faces a choice of plans.

Life Insurance Lapsation (f_i^7). This friction imposes a direct dollar loss $\ell_7(a_{it}, \delta_i)$ that is subtracted from the liquid account each period, representing the savings foregone by lapsing early on a long-duration term life insurance policy rather than purchasing a shorter-duration policy. The dollar loss varies by age and permanent income group, calibrated from SCF data on TLI holdings and Gottlieb and Smetters (2021) lapsing rates; see Table 2 for the prevalence and loss estimates by income group. Because the model does not explicitly model the life insurance decision, the loss is assigned as an average over the population of individuals with the friction without distinguishing who holds life insurance coverage.

Smoking (f_i^8). This friction operates by scaling the mortality hazard by an age- and income-group-dependent multiplicative factor $\kappa(a_{it}, \delta_i)$:

$$(1 - \mathscr{D}) \mapsto (1 - \mathscr{D}) \times \kappa(a_{it}, \delta_i) \tag{35}$$

The scaling factor varies across age groups and permanent income groups, so that the mortality effect of smoking differs by socioeconomic status and age. The mortality multipliers are calibrated from NHIS data, with factors of approximately 2.3 for ages 50–74 and 1.9 for ages 75+; see Table 2 for the prevalence estimates by income group. We do not model any income loss from cigarette purchases or lost work time, so the friction operates exclusively through the mortality channel.

Total dollar loss. The total dollar loss from frictions in period t is:

$$\mathscr{L}_{it}(\mathbf{f}_i) = \sum_{j \in \mathscr{J}} f_i^j \cdot \ell_j(a_{it}, \delta_i) \tag{36}$$

where $\mathscr{J} = \{4, 5, 6, 7\}$ is the set of frictions that impose direct dollar losses. These dollar losses are subtracted from liquid savings before computing returns, as shown in (13).

Definition of total income. We define an individual's "total income" as follows:

$$\mathscr{Y}_{it} = y_{it} \cdot \mathbf{1}_{a_{it} < a_R} + T_{it}^{\text{eitc}} + T_{it}^{\text{snap}} + T_{it}^{\text{ssi}} + T_{it}^{ss} + T_{it}^{I} - T_{it}^{sd} + T_{it}^{\text{floor}} - \mathscr{T}_y\big(y_{it}^{\text{gross}}\big) - \mathscr{L}_{it}(\mathbf{f}_i) \tag{37}$$

Total income, $\mathscr{Y}_{it}$, equals total transfers T_{it} plus working-life labor income, with two modifications. First, we subtract friction dollar losses $\mathscr{L}_{it}(\mathbf{f}_i)$, which are not part of T_{it} but reduce an individual's effective resources. Second, we replace the income tax $T_{it}^y = \mathscr{T}_y(y_{it}^T)$, which is levied on taxable income y_{it}^T that reflects 401(k) contributions and withdrawals, with $\mathscr{T}_y(y_{it}^{\text{gross}})$, which is levied on gross income alone. This ensures that the tax consequences of 401(k) transactions do not appear in $\mathscr{Y}_{it}$, given that the 401(k) flows themselves are excluded.

When we show results of the impact of frictions on income below, $\mathscr{Y}_{it}$ is the metric we report. The benefit of this measure is that it captures the impact of a friction on the entire set of inflows and outflows that an individual receives in a given period — including labor income, government transfers, tax obligations, student debt payments, inheritances, and friction losses — while isolating these flows from intertemporal choices, such as 401(k) contributions and withdrawals, which will show up when we study effects on wealth accumulation and consumption.

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 allows 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.

9.3 Plan to Incorporate Remaining Frictions

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

Not Contributing to 401(k). Individuals with 401(k) access who have this friction do not contribute to the illiquid account, behaving as if they lack 401(k) access entirely. In the counterfactual that removes the friction, these individuals switch to optimally choosing contributions, benefiting from the employer match and the tax advantages of the account. The share at risk s is the share with 401(k) access, and f is calibrated from administrative W-2 data on contribution rates (Choukhmane et al., 2023; Myers et al., 2024); see Table 2 for the values by income group.

Under-Diversification. 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. The prevalence and dollar losses are estimated from SCF data on individual stock holdings; see Table 2.

Excessive Mutual Fund Fees. All individuals will face a reduction in the return on their equity portfolio equal to the average excess mutual fund fee (approximately 41 basis points), rescaled by the share of equity held in mutual funds. This friction applies universally ($f = 1$) given evidence that nearly all investors are insensitive to mutual fund fees (Choi et al., 2010). The excess fee is computed from CRSP mutual fund data; see Table 2.

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. The share of homeowners s is measured from the SCF, and the probability of being "asleep" f is calibrated from Andersen et al. (2020); L is estimated from refinancing simulations using historical US interest rate data; see Table 2.

Suboptimal Credit Card Debt Repayment. 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 by 1.7 percentage points for individuals with the friction, consistent with the estimated cost of suboptimal repayment allocation across multiple cards (Gathergood et al., 2019). The prevalence f is estimated from Gathergood et al. (2019); see Table 2. To generate meaningful borrowing, we plan to incorporate naive present bias (Laibson et al., 2024).

Not Claiming EITC and SNAP. We will model this friction by withholding EITC (or SNAP) payments from affected individuals. Individuals with the friction will simply not receive this transfer. The share eligible s and the non-

claiming rate f are calibrated from PSID data and IRS administrative records (Coleman et al., 2024; Vigil, 2022); L is the average foregone benefit conditional on eligibility; see Table 2.

Not Screening for Colon Cancer. We will model this friction similar to the effects of smoking: failure to undergo colorectal cancer screening will increase the age-specific mortality hazard by 28% of the CRC-specific mortality rate at that age, based on the meta-analysis of screening RCTs. The share at risk s and the non-screening rate f are estimated from NHIS data; see Table 2.

9.4 Calibration

This section describes how we simulate from the model can calibrate its parameters. 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.

Simulation procedure. The model is solved and simulated separately for each of the 2^N possible friction combinations, with identical realizations of stochastic shocks across all combinations.[44] Because the number of combinations grows exponentially in the number of frictions, this is computationally intensive.[45] To construct the baseline simulation, we map the empirical prevalence estimates s and f from Table 2 to model state variables (permanent income groups) using an OLS projection based on the conditional probability of each model state variable given the observable income measure, where these conditional probabilities are computed from a preliminary simulation of the income process. For the frictions that are modeled as direct dollar losses (f^4 through f^7), we additionally map the age-specific dollar losses L from the empirical estimates to model state variables using the same projection, producing the age- and income-group-dependent loss functions $\ell_j(a_{it}, \delta_i)$ described above. We then use the projected prevalence probabilities to assign each simulated individual a permanent friction combination, with all frictions drawn independently. For each individual, we select the simulation results corresponding to their assigned friction combination, producing a baseline panel dataset that reflects the estimated friction prevalence in the population.

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 89, corresponding to $a_R = 43$ and $a_T = 67$. 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 $\alpha_n =$

[44] 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.

[45] The model is coded in C++ and compiled with GPU acceleration in order to solve and simulate in a feasible amount of time.

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.

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. The stochastic parameters of the income process — persistence ρ_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 $v_{\text{cond}} = 0.2$.

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 $\tau_p = \$475$ in numeraire units for all income groups, which is calibrated to match average participation 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 eeducaion 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. 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 τ_{pref} is a step function of AGI and the preferential share ω_{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).

9.5 Model Fit

Table 4 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 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, though the model somewhat overstates incomes for the high income group.

Turning to wealth accumulation, the model substantially overstates total wealth relative to the SCF at all ages and percentiles. This is primarily due to two forces. First, the discount factor is too high, particularly for lower income individuals, which generates excessive savings. We plan to address this in future versions by incorporating income-group-specific discount factors and potentially present bias. Second, the model vastly overstates 401(k) wealth accumulation: mean 401(k) wealth at age 45 is approximately $182,000 in the model relative to approximately $57,000 in the data, and the discrepancy is similar at age 65. This reflects the fact that the 401(k) participation friction has not yet been incorporated into the model — the model generates 401(k) participation rates that far exceed observed participation rates in the NCS, which is consistent with the model lacking a friction that deters participation. However, the model does generate a reasonable share of early 401(k) withdrawals — 20% relative to the 25% estimated by Argento et al. (2015).

The model matches observed stock market participation rates well across income groups: at age 45, model participation rates of 0.48, 0.82, and 0.88 for low, middle, and high income groups are close to the SCF values of 0.46, 0.71, 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 0.44, 0.74, and 0.76 relative to data values of 0.43, 0.46, and 0.46 — 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. The frictionless participation rate of 0.89 in the model is close to the estimate of 0.92, and the frictionless mean equity share of 0.79 matches the estimate almost exactly. These moments are computed in the model after turning off only the stock market participation friction, holding all other frictions at their baseline prevalence.

10 Counterfactuals: Effects of Removing Each Friction

This section presents the results from counterfactuals in which we turn off each friction independently to study its effects.fects. 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.[46]

10.1 Impact by Income Group

Table 5 reports the percent change in undiscounted lifetime total income, undiscounted lifetime consumption, and wealth at ages 40 and 65 from removing each friction, separately by permanent income group. Total income is defined in (37); the corresponding level differences are reported in Table H1 in the appendix.

[46] 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.

The largest lifetime impacts on consumption come from removing the stock market participation and smoking frictions. Removing the stock market participation friction raises lifetime consumption by approximately 2% for the low income group and 3.1% for the middle income group, with a smaller effect of 1.8% for the high income group. The effects on wealth are even more pronounced: wealth at age 65 increases by approximately 11.8% for the low income group, 7.4% for the middle income group, and 3.4% for the high income group. 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 H1), the pattern is reversed: removing stock market participation raises wealth at age 65 by approximately $5,800 for the low income group, $36,400 for the middle income group, and $47,100 for the high income group.

Removing the smoking friction generates large gains in lifetime consumption — approximately 1% for the low income group and 0.7% for the middle income group — and substantial increases in wealth at retirement, particularly for the low income group (approximately 3% at age 65). These effects operate primarily through the mortality channel: individuals who would have died earlier due to smoking now survive into retirement, accumulating additional years of consumption. These additional years of life lead to increase 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 the largest of any friction for the middle and high income groups ($19,200 and $17,700, respectively).

The education frictions — college attendance and 2-year for-profit attendance — generate moderate lifetime impacts that are broadly similar in magnitude. Removing the college attendance friction raises lifetime total income by 0.4–0.5% for the low and middle income groups, with a smaller effect of 0.1% for the high income group. The effects on lifetime consumption are similar in magnitude. The for-profit attendance friction generates somewhat larger percent effects, particularly for the low income group (0.6% for both income and consumption), reflecting the fact that this friction is concentrated among lower-income individuals. Both education frictions generate positive effects on wealth at age 65, consistent with the higher lifetime earnings enabling greater wealth accumulation.

The direct dollar loss frictions — dominated insurance, credit card late fees, overdraft fees, and life insurance lapsation — generate effects that are roughly proportional to their empirical dollar losses documented in Table 2. Removing the dominated insurance friction raises lifetime total income by 0.3–0.5% for the low and middle income groups, while removing overdraft fees has a similar effect (0.3% for the low income group). Credit card late fees and life insurance lapsation generate smaller effects, consistent with their lower estimated dollar losses. An notable feature of these frictions is that they tend to generate negative effects on wealth at ages 40 and 65, despite raising lifetime total income and consumption. This reflects the fact that removing these frictions increases disposable income, which the model's agents partially consume rather than save, leading to a reallocation from savings toward consumption.

10.2 Impact on Total Inequality

Table 6 reports the impact of each friction on population-wide measures of inequality in undiscounted lifetime total income, undiscounted lifetime consumption, and wealth at age 65. Panel A reports level differences and Panel B reports percent differences. In interpreting these results, a negative change in the Gini or SD Log indicates that removing the friction reduces inequality in that outcome, while a positive change in the P75–P25 or P90–P10 wealth spread indicates that removing the friction widens the wealth distribution.

Looking across all the frictions, a common pattern emerges: removing a friction tends to reduce inequality in lifetime total income and consumption while simultaneously increasing inequality in wealth. This pattern is most pronounced for stock market participation, the education frictions, and smoking, but appears to varying degrees across nearly all frictions. We discuss each group in turn.

Removing the stock market participation friction has the largest effect on wealth inequality. The P75–P25 wealth spread at age 65 increases by approximately $53,700 (6.5%) and the P90–P10 spread increases by approximately $77,900 (4.7%). This reflects the fact that higher-wealth individuals benefit more in absolute terms from access to the equity premium, widening the wealth distribution even as the friction is removed for everyone. The effects on income inequality are negligible (the Gini of income falls by only 0.0001), while the standard deviation of log consumption increases by 0.006 (0.7%), suggesting that the additional wealth translates into greater consumption dispersion.

The education frictions and smoking generate a similar dual pattern. Removing the for-profit attendance friction reduces the Gini of income by 0.0012 (0.3%) and the Gini of consumption by 0.0011 (0.3%), consistent with the fact that this friction disproportionately affects lower-income individuals whose income and consumption increase when the friction is removed. However, the P75–P25 wealth spread increases by approximately $4,100 (0.5%), reflecting the fact that individuals who benefit from removing the friction also save more, and those with higher baseline wealth accumulate more in absolute terms. The college attendance friction generates a similar pattern, with the P75–P25 wealth spread increasing by approximately $3,800 (0.5%). Removing the smoking friction reduces the Gini of income by 0.0011 (0.3%) and the SD Log of income by 0.0024 (0.3%), with corresponding reductions in consumption inequality, while increasing the P75–P25 and P90–P10 wealth spreads by approximately $3,100 (0.4%) and $7,600 (0.5%), respectively.

The direct dollar loss frictions generate smaller effects. Removing the dominated insurance friction reduces the Gini of income by 0.0007 (0.2%) and the Gini of consumption by 0.0006 (0.2%). Overdraft fees and credit card late fees generate even smaller reductions in income and consumption inequality, with Gini changes of 0.0004 and 0.0002, respectively. The wealth effects of these frictions are mixed in sign and small in magnitude, consistent with their relatively modest per-period dollar losses. Life insurance lapsation has a negligible effect on all inequality measures.

11 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 17 frictions spanning education, savings, borrowing, insurance, benefit claiming, and health, and find that these frictions disproportionately affect lower-income individuals: the aggregate impact on annual income is approximately 9% for the bottom quartile relative to approximately 3% for the top quartile. The total loss for low-income households is approximately seven times larger than the income effect of a major EITC expansion. We incorporate these frictions into a life cycle model and find that removing them tends to reduce inequality in lifetime income and consumption across income groups, with smoking and for-profit college attendance generating the largest effects on consumption inequality.

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.

Tables

Table 2: 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				
Low Income	0.491	0.204	\$924.67	\$88.49
Middle Income	0.221	0.204	\$5,677.70	\$268.82
High Income	0.067	0.204	\$12,312.71	\$144.71
Panel B: Attending 2-Year For-Profit Colleges				
Low Income	0.290	0.231	\$1,329.22	\$52.66
Middle Income	0.321	0.138	\$4,969.11	\$247.73
High Income	0.123	0.091	\$10,365.28	\$209.18
Panel C: Not Investing in the Stock Market				
Low Income	0.422	0.623	\$262.27	\$68.82
Middle Income	0.725	0.310	\$833.63	\$187.05
High Income	0.913	0.144	\$2,541.35	\$333.35
Panel D: Under-Diversification				
Low Income	0.388	0.024	\$1,790.34	\$17.00
Middle Income	0.560	0.041	\$2,686.36	\$61.43
High Income	0.783	0.061	\$8,458.44	\$403.86
Panel E: Excessive Mutual Fund Fees				
Low Income	0.187	1.000	\$182.50	\$34.14
Middle Income	0.573	1.000	\$295.27	\$169.05
High Income	0.819	1.000	\$1,370.46	\$1,123.08
Panel F: Failure to Refinance Mortgage				
Low Income	0.159	0.849	\$422.86	\$76.37
Middle Income	0.400	0.716	\$299.35	\$120.42
High Income	0.549	0.689	\$510.52	\$261.05

Continued on next page

Table 2 – continued from previous page

Income Group (j)	s_j	f_j	L_j	$s_j \cdot f_j \cdot L_j$
Panel G: Suboptimal Credit Card Repayments				
Low Income	0.152	0.880	\$102.12	\$12.92
Middle Income	0.319	0.880	\$150.16	\$34.85
High Income	0.215	0.880	\$259.30	\$43.80
Panel H: Paying Overdraft Fees				
Low Income	0.800	0.420	\$308.66	\$104.09
Middle Income	0.960	0.372	\$283.09	\$100.95
High Income	0.992	0.189	\$243.19	\$45.18
Panel I: Paying Late Fees				
Low Income	0.491	0.294	\$386.59	\$54.24
Middle Income	0.741	0.266	\$386.59	\$74.63
High Income	0.838	0.136	\$386.59	\$43.43
Panel J: Choosing Dominated Health Insurance				
Low Income	0.078	0.620	\$1,121.00	\$54.21
Middle Income	0.215	0.520	\$1,121.00	\$125.33
High Income	0.271	0.400	\$1,121.00	\$121.52
Panel K: Lapsing Life Insurance				
Low Income	0.125	0.180	\$51.78	\$1.00
Middle Income	0.286	0.170	\$114.89	\$4.60
High Income	0.355	0.158	\$289.09	\$12.72
Panel L: Failing to Claim EITC				
Low Income	0.549	0.200	\$1,195.04	\$131.21
Middle Income	0.137	0.200	\$1,456.37	\$39.98
High Income	0.006	0.200	\$850.07	\$0.97
Panel M: Failing to Claim SNAP				
Low Income	0.689	0.180	\$2,798.26	\$347.16
Middle Income	0.204	0.180	\$2,262.80	\$83.01

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Table 2 – continued from previous page

Income Group (j)	s_j	f_j	L_j	$s_j \cdot f_j \cdot L_j$
High Income	0.081	0.180	\$2,075.24	\$30.40
Panel N: Failing to take Statins				
Low Income	0.427	0.469		
Middle Income	0.410	0.402	22.3% higher cardiovascular mortality	
High Income	0.434	0.357		
Panel O: Failing to do Colorectal Cancer Screenings				
Low Income	0.503	0.621	28% higher mortality due to colorectal cancer	
Middle Income	0.504	0.528		
High Income	0.507	0.444		
Panel P: Failing to Quit Smoking				
Low Income (Bottom 25%)	0.425	0.557	Increased mortality by 2.27 from 50-74, 1.95 from 75+	
Middle Income (Middle 25%-75%)	0.409	0.150	Increased mortality by 2.53 from 50-74, 1.79 from 75+	
High Income (Top 25%)	0.319	0.234	Increased mortality by 2.06 from 50-74, 2.12 from 75+	

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.

Table 3: Decision-Making Frictions, Data Sources Summarized

No.	Category	Friction	s_j Data Source	f_j Data Source	L_j Data Source	Income Measure
1	Education	Not Attending College Due to Frictions	PSID	Prior Literature	Mountjoy (2025) + Model	Permanent Income Group
2	Education	Attending 2-Year For-Profit Colleges	PSID	NCES + BPS	Cellini and Turner (2019) + NCES + Model	Parental Income
3	Savings	Not Meeting the Employer 401(k) Match				
4	Savings	Not Investing in the Stock Market	SCF	SCF	SCF	Current Income
5	Savings	Under-Diversification	SCF	SCF	SCF	Current Income
6	Savings	Investing in High-Fee Mutual Funds	SCF	Choi et al. (2010)	CRSP + SCF	Current Income
7	Borrowing	Suboptimally Repaying Credit Card Debt	SCF	Gathergood et al. (2019)	Gathergood et al. (2019) + SCF	Current Income
8	Borrowing	Not Refinancing the Mortgage	SCF	Andersen et al. (2020)	House Purchases Simulation	Current Income
9	Borrowing	Incurring Overdraft Fees	CFPB	CFPB	CFPB	Current Income
10	Borrowing	Incurring Late Payment Fees	CFPB	CFPB	CFPB + Low et al. (2017)	Current Income
11	Insurance	Choosing Dominated Insurance Plans	SCF + Liu and Sydnor (2022)	Bhargava et al. (2017)	Liu and Sydnor (2022)	Current Income
12	Insurance	Suboptimally Lapsing Life Insurance	SCF	Gottlieb and Smetters (2021) + SCF	Compulife + SCF	Current Income
13	Benefits	Not Claiming EITC Benefits	PSID	Coleman et al. (2024)	PSID Simulation	Current Income
14	Benefits	Not Claiming SNAP Benefits	PSID	Vigil (2022)	PSID Simulation	Current Income
15	Health	Not Doing Colorectal Cancer Screenings	Recommended Screening Guidelines + PSID	NHIS	Shroff et al. (2014) + Model	Current Income
16	Health	Failing to Take Statin Medications	NHIS	Verma et al. (2017)	Prior Literature + Model	Current Income
17	Health	Failing to Quit Smoking	NHIS	NHIS	NHIS + Model	Current Income

Table 4: Comparison of Model and Data Moments

Moment Description	Model Value	Data Value	Data Source
Median Income at Age 25, Low Income	$8,121	$8,240	PSID
Median Income at Age 25, Middle Income	$31,228	$28,890	PSID
Median Income at Age 25, High Income	$81,300	$60,888	PSID
Median Income at Age 35, Low Income	$9,950	$13,677	PSID
Median Income at Age 35, Middle Income	$45,104	$44,182	PSID
Median Income at Age 35, High Income	$128,108	$85,049	PSID
Median Income at Age 45, Low Income	$9,731	$12,656	PSID
Median Income at Age 45, Middle Income	$48,716	$42,594	PSID
Median Income at Age 45, High Income	$136,825	$89,557	PSID
Median Income at Age 55, Low Income	$7,134	$5,450	PSID
Median Income at Age 55, Middle Income	$41,722	$39,597	PSID
Median Income at Age 55, High Income	$123,606	$88,891	PSID
Median Total Wealth at Age 25	$26,885	$4,176	SCF
Median Total Wealth at Age 45	$152,795	$62,484	SCF
Median Total Wealth at Age 65	$394,313	$172,767	SCF
P10 Total Wealth at Age 45	$11,149	-$4,377	SCF
P10 Total Wealth at Age 65	$6,468	$780	SCF
P75 Total Wealth at Age 45	$414,608	$250,279	SCF
P75 Total Wealth at Age 65	$964,302	$533,349	SCF
Median Liquid Wealth at Age 45	$74,694	$10,530	SCF
Median Liquid Wealth at Age 65	$78,470	$21,362	SCF
401(k) Participation at Age 45, Low Income	0.48	0.23	NCS
401(k) Participation at Age 45, Middle Income	0.71	0.53	NCS
401(k) Participation at Age 45, High Income	0.84	0.75	NCS
Mean 401(k) Wealth at Age 45	$182,204	$56,546	SCF
Mean 401(k) Wealth at Age 65	$521,096	$120,584	SCF
Share with Early 401(k) Withdrawals	0.20	0.25	ABS15
Stock Market Participation at Age 45, Low Income	0.48	0.46	SCF
Stock Market Participation at Age 45, Middle Income	0.82	0.71	SCF
Stock Market Participation at Age 45, High Income	0.88	0.88	SCF
Mean Stock Share at Age 45, Low Income	0.44	0.43	SCF
Mean Stock Share at Age 45, Middle Income	0.74	0.46	SCF
Mean Stock Share at Age 45, High Income	0.76	0.46	SCF
Stock Market Participation at Age 45 (Frictionless)	0.89	0.92	CD26
Mean Stock Share at Age 45 (Frictionless)	0.79	0.79	CD26

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 final two rows (frictionless stock market participation and equity share), which are computed after turning off only the stock market participation friction. Data sources: PSID (Panel Study of Income Dynamics), SCF (Survey of Consumer Finances), NCS (National Compensation Survey), ABS15 (Argento et al., 2015), CD26 (Choukhmane and de Silva, 2026).

Table 5: Model Results: Lifetime Friction Impact

Income Group (j)	ΔTotal Income$_{lt}$	ΔConsumption$_{lt}$	ΔWealth$_{40}$	ΔWealth$_{65}$
Panel A: College Attendance				
Low	0.390%	0.315%	-0.048%	0.966%
Middle	0.459%	0.450%	0.476%	0.680%
High	0.120%	0.122%	0.146%	0.163%
Panel B: 2-Year For-Profit Attendance				
Low	0.629%	0.647%	0.859%	1.641%
Middle	0.481%	0.489%	0.414%	0.760%
High	0.100%	0.101%	0.090%	0.136%
Panel C: Stock Market Participation				
Low	-0.032%	2.005%	5.879%	11.845%
Middle	-0.049%	3.145%	5.143%	7.412%
High	-0.037%	1.843%	2.512%	3.405%
Panel D: Overdraft Fees				
Low	0.280%	0.243%	-0.191%	-0.187%
Middle	0.124%	0.099%	-0.134%	-0.068%
High	0.007%	0.005%	-0.014%	-0.004%
Panel E: Credit Card Late Fees				
Low	0.127%	0.112%	-0.070%	-0.080%
Middle	0.087%	0.071%	-0.095%	-0.046%
High	0.009%	0.006%	-0.015%	-0.004%
Panel F: Dominated Insurance Choice				
Low	0.448%	0.411%	-0.254%	0.662%
Middle	0.346%	0.285%	-0.385%	0.218%
High	0.133%	0.101%	-0.201%	0.054%
Panel G: Life Insurance Lapsation				
Low	-0.000%	-0.001%	0.003%	0.000%

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Table 5 – continued from previous page

Income Group (j)	ΔTotal Income$_{lt}$	ΔConsumption$_{lt}$	ΔWealth$_{40}$	ΔWealth$_{65}$
Middle	0.004%	0.003%	-0.009%	-0.000%
High	0.031%	0.021%	-0.112%	0.022%
Panel H: Smoking				
Low	0.807%	0.995%	0.262%	2.959%
Middle	0.383%	0.711%	0.115%	1.191%
High	0.132%	0.337%	0.045%	0.398%

Notes: Each panel reports the average lifetime impact of removing a single friction, expressed as a percent change. All variables with subscript lt denote undiscounted lifetime sums. ΔTotal Income$_{lt}$ is the percent change in the undiscounted lifetime sum of total income, as defined in (37). ΔConsumption$_{lt}$ is the percent change in the undiscounted lifetime sum of consumption. ΔWealth$_{40}$ and ΔWealth$_{65}$ are percent changes in total wealth (liquid plus 401(k) assets) at ages 40 and 65, respectively. Each entry is computed as the difference between the mean frictionless outcome and the mean baseline outcome within the income group, divided by the mean baseline outcome. See Table H1 for the corresponding level differences.

Table 6: Model Results: Effects of Removing Frictions on Total Inequality

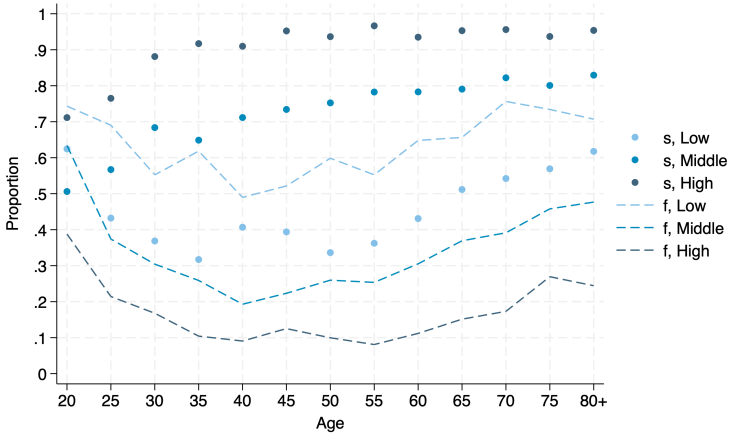
Outcome	Total Income$_{lt}$		Consumption$_{lt}$		Wealth$_{65}$	
Inequality Metric	Δ Gini	Δ SD Log	Δ Gini	Δ SD Log	Δ P75–P25	Δ P90–P10
Panel A: Level Differences						
Stock Market Participation	-0.0001	-0.0001	0.0000	0.0058	$53,734	$77,877
Dominated Insurance Choice	-0.0007	-0.0016	-0.0006	-0.0017	$636	$1,330
Credit Card Late Fees	-0.0002	-0.0004	-0.0002	-0.0005	-$217	$577
Overdraft Fees	-0.0004	-0.0010	-0.0003	-0.0010	-$352	-$383
Life Insurance Lapsation	0.0000	0.0001	0.0000	0.0000	-$38	$0
2-Year For-Profit Attendance	-0.0012	-0.0017	-0.0011	-0.0016	$4,120	$4,077
College Attendance	-0.0009	-0.0013	-0.0008	-0.0004	$3,788	$4,596
Smoking	-0.0011	-0.0024	-0.0010	-0.0018	$3,117	$7,645
Panel B: Percent Differences						
Stock Market Participation	-0.018%	-0.019%	0.005%	0.676%	6.549%	4.672%
Dominated Insurance Choice	-0.201%	-0.206%	-0.159%	-0.195%	0.077%	0.080%
Credit Card Late Fees	-0.059%	-0.058%	-0.044%	-0.053%	-0.026%	0.035%
Overdraft Fees	-0.108%	-0.129%	-0.080%	-0.113%	-0.043%	-0.023%
Life Insurance Lapsation	0.007%	0.009%	0.004%	0.004%	-0.005%	0.000%
2-Year For-Profit Attendance	-0.325%	-0.223%	-0.267%	-0.184%	0.502%	0.245%
College Attendance	-0.254%	-0.169%	-0.189%	-0.052%	0.462%	0.276%
Smoking	-0.304%	-0.313%	-0.259%	-0.211%	0.380%	0.459%

Notes: This table reports the impact of each friction on population-wide inequality in lifetime outcomes. All variables with subscript lt denote undiscounted lifetime sums. Total income is defined in (37). 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 "Outcome" row indicates the outcome whose distribution is being measured, and the "Inequality Metric" row indicates the specific distributional statistic. Panel A reports level differences; Panel B reports percent differences relative to the baseline statistic. Gini is the Gini coefficient. SD Log is the standard deviation of the log of the outcome. P75–P25 and P90–P10 are interquartile and interdecile spreads of wealth at age 65, respectively.

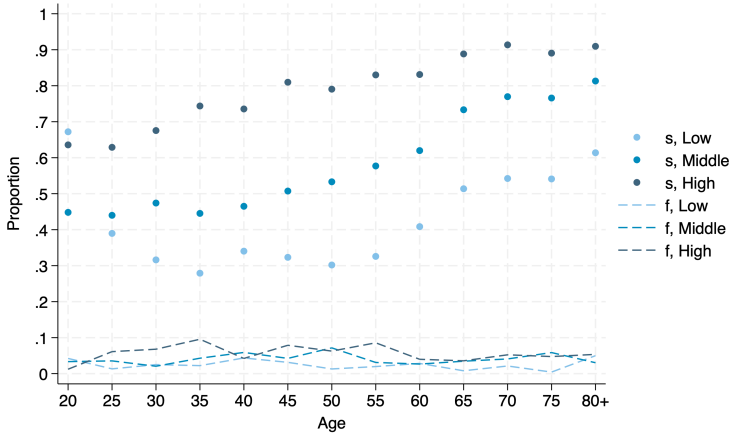
Figures

Figure 1: Empirical Evidence of all Frictions

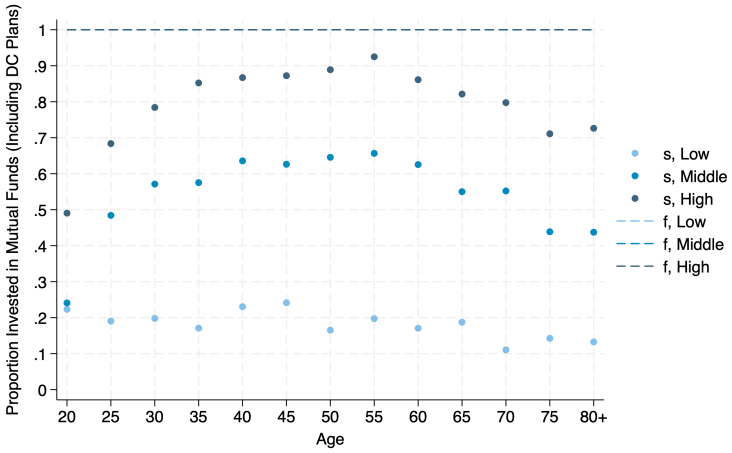
(a) Panel A: Not Investing in the Stock Market



(b) Panel B: Under-Diversification



(c) Panel C: Excessive Mutual Fund Fees



(d) Panel D: Failure to Refinance Mortgage

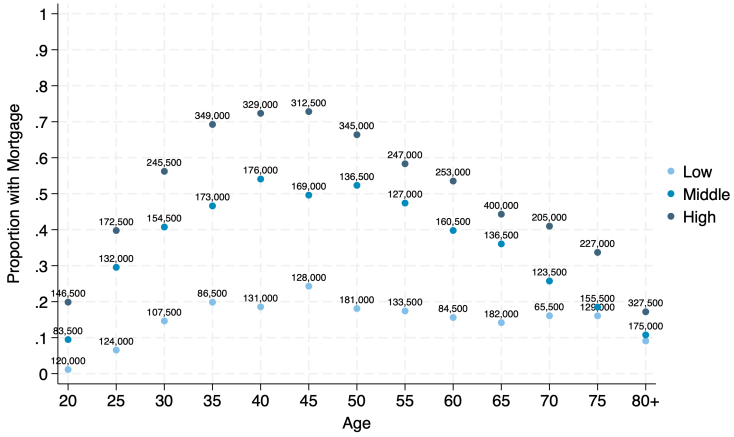
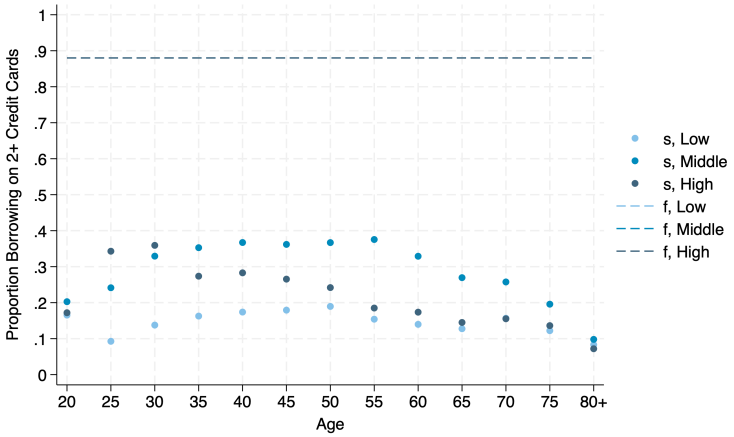
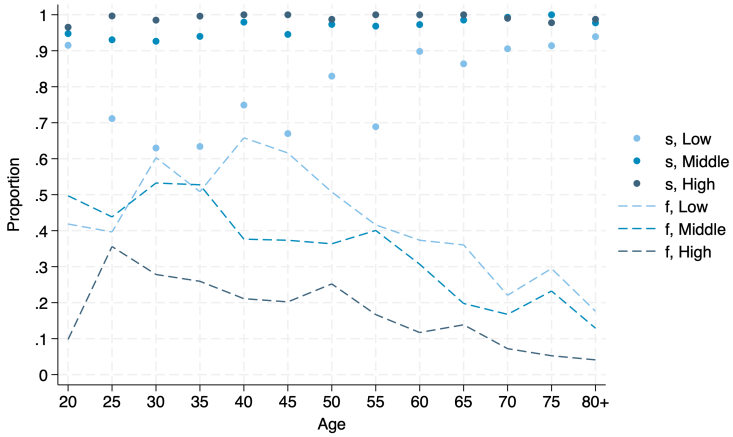


Figure 1: Empirical Evidence of all Frictions (Continued)

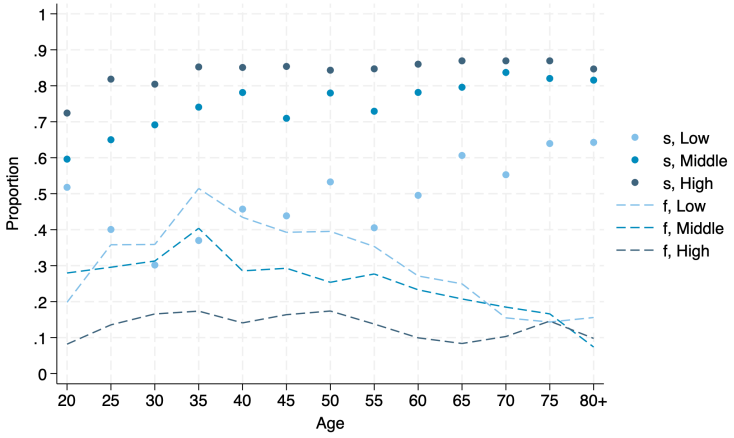
(e) Panel E: Suboptimal Credit Card Repayments



(f) Panel F: Paying Overdraft Fees



(g) Panel G: Paying Late Fees



(h) Panel H: Choosing Dominated Health Insurance

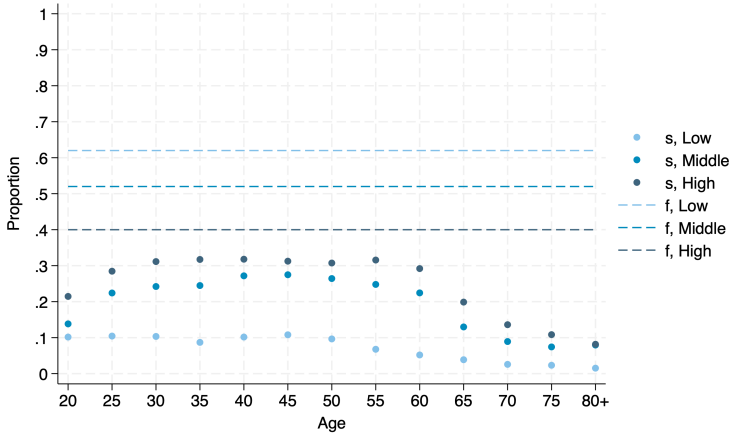
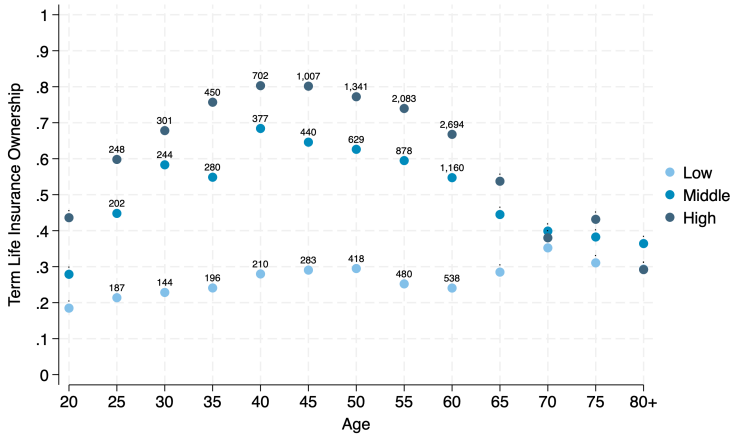
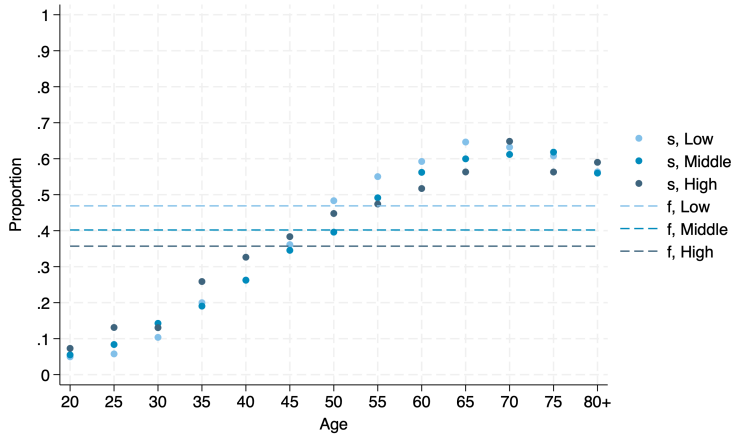


Figure 1: Empirical Evidence of all Frictions (Continued)

(i) Panel I: Lapsing Life Insurance



(j) Panel J: Failing to take Statins



(k) Panel K: Failing to do Colorectal Screenings

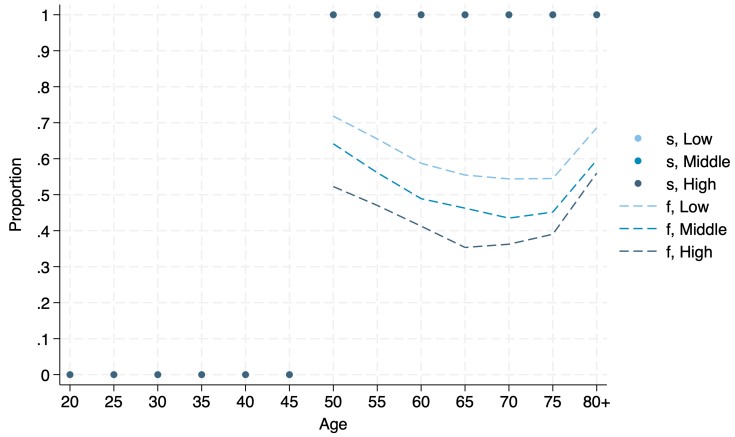
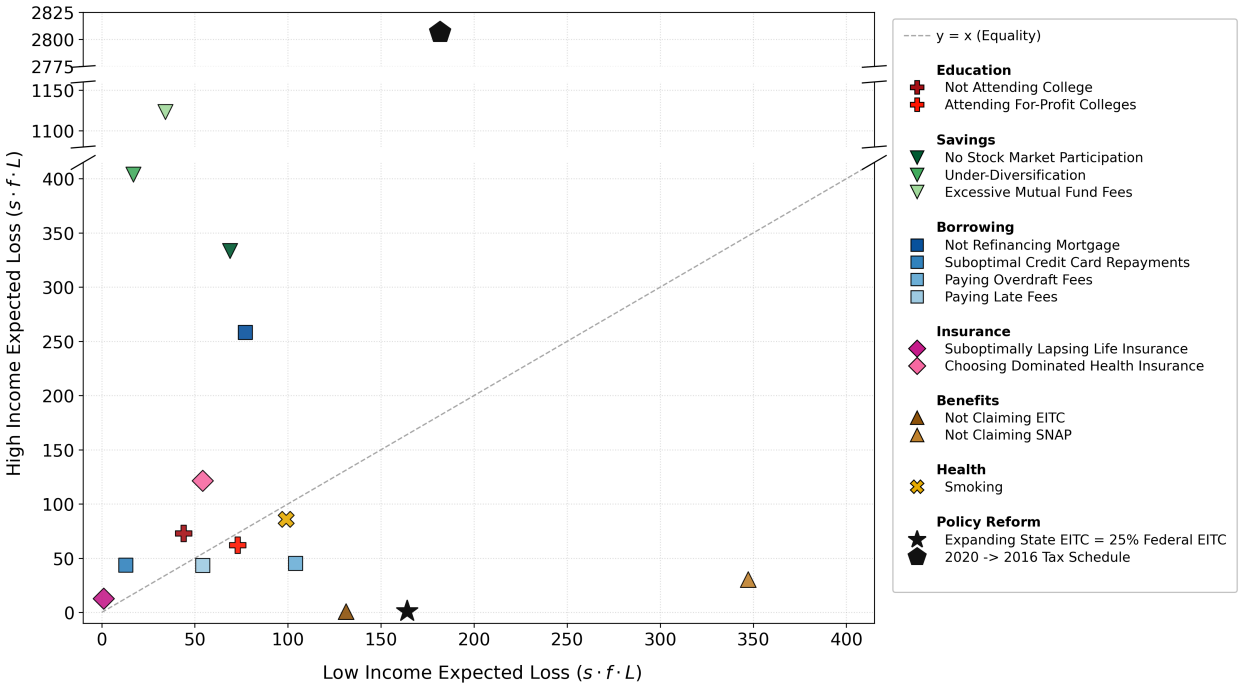
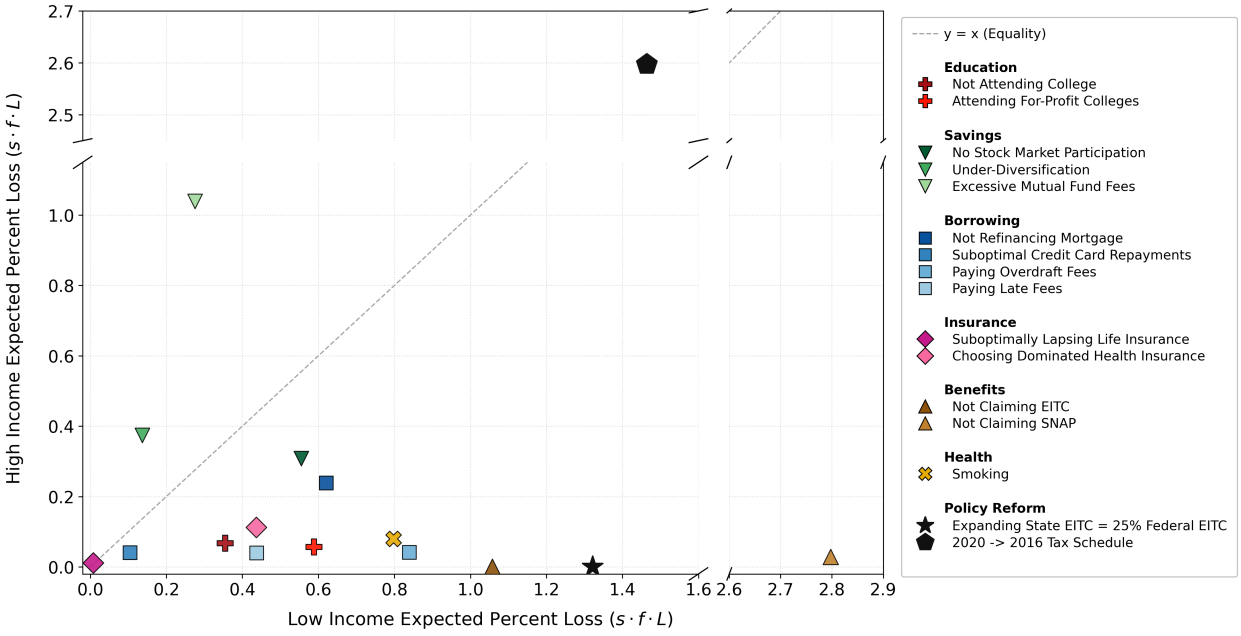


Figure 2: Expected Annual Losses Across Frictions



(a) Dollar Losses



(b) Losses as a Percentage of Post-Tax Income

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 income in our model. We divide the low-income group's losses by $12,409, the middle-income group's losses by $53,843, and the high-income group's losses by $108,067.

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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. Education Frictions

Table A1: College Attendance Regressions

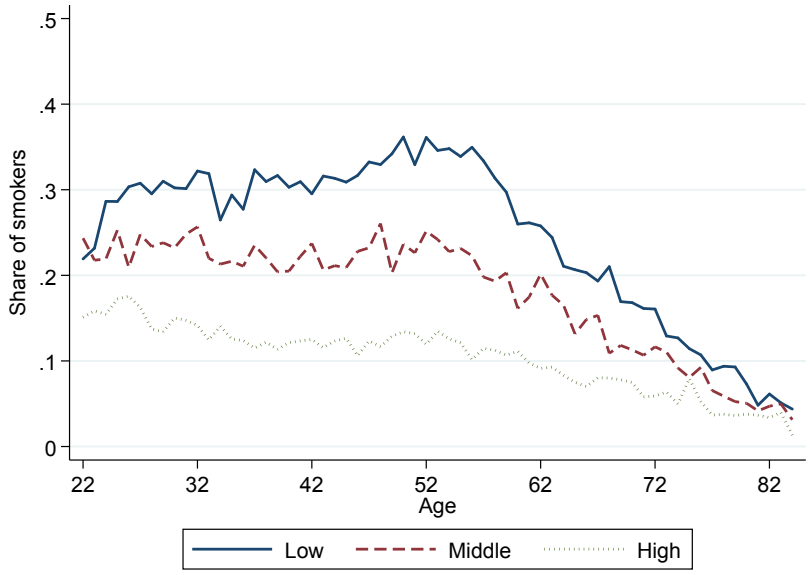
	Attending Any College		
	(1)	(2)	(3)
Intercept	0.592***		
	(0.015)		
Middle Parental Income (32%-75%)	0.150***	0.048***	0.068***
	(0.019)	(0.017)	(0.017)
High Parental Income (75%+)	0.302***	0.127***	0.159***
	(0.017)	(0.015)	(0.015)
Academic GPA FE		✓	✓
Math Cognitive Test FE		✓	✓
School FE			✓
Sex FE			✓
Race FE			✓
Observations	12210	12210	12210
R^2	0.082	0.270	0.280
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A2: 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

Appendix B. Failing to Quit Smoking

Figure B1: Share of Smokers by Age and Income Group

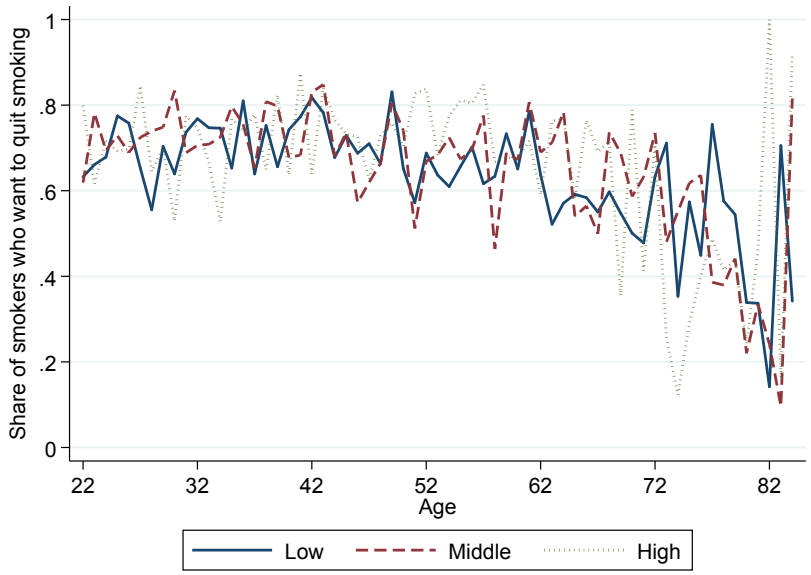


Notes: The shares are estimated using 2010-2018 data from the NHIS. The Low, Middle, and High income groups correspond to the bottom 25%, middle 50%, and top 25% of the household income distribution.

Table B1: Smoking Friction Losses Summary

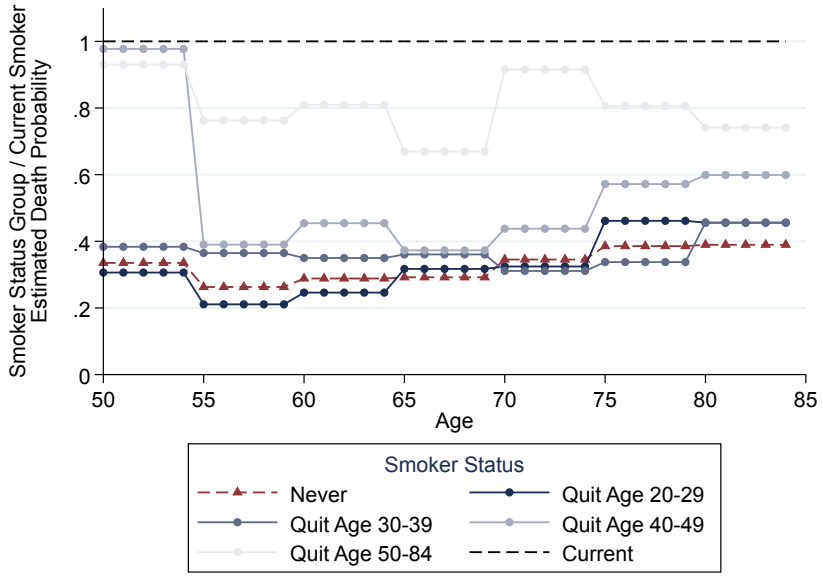
Income Group	s Share Wanting to Quit by 50	f Share Failing to Quit by 50	$L_{50\text{-}74}, L_{75+}$ Increased mortality factor (50-74, 75+)	L_{Income} Expected income loss
Low Income (Bottom 25%)	0.425	0.557	2.27, 1.95	1.95
Middle Income (Middle 25%-75%)	0.409	0.150	2.53, 1.79	1.79
High Income (Top 25%)	0.319	0.234	2.06, 2.12	2.12

Figure B2: Share of Current Smokers Wanting to Quit by Age and Income Group



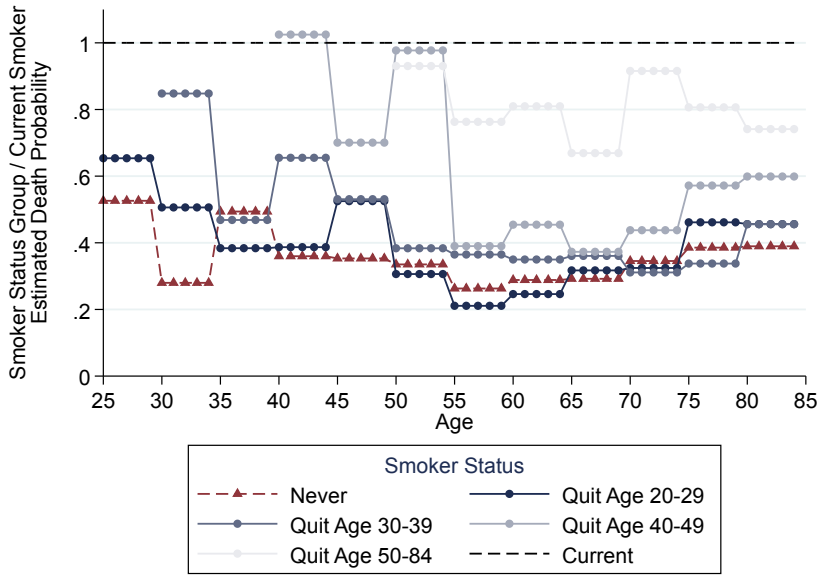
Notes: The shares are estimated using 2010-2018 data from the NHIS. The Low, Middle, and High income groups correspond to the bottom 25%, middle 50%, and top 25% of the household income distribution.

Figure B3: 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 B4: Mortality of Former and Never Smokers Relative to Current Smokers, All Ages



Notes: One-year death probabilities are estimated using 2010-2018 data from the NHIS. The ratios are averaged across five-year bins.

Appendix C. Poor Portfolio Choice

Under-Diversification 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 $\sigma_m^2 \equiv \mathrm{Var}(r_m)$. Define $\sigma^2 \equiv \mathbb{E}[\mathrm{Var}(r_i)]$ as the average individual-stock return variance and $\rho \equiv \mathbb{E}[\mathrm{Cov}(r_i, r_j)]$ 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

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

Under the CAPM, $r_i = \beta_i r_m + \varepsilon_i$ with $\mathrm{Cov}(\varepsilon_i, \varepsilon_j) = 0$. 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

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

Using the Arrow–Pratt approximation for multiplicative risks with coefficient of relative risk aversion γ, 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 $L_d = W L_r = \frac{\gamma}{2}\frac{H^2}{W} L_v$.

Table C1: Under-Diversification 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
Lower	0.388	0.053	\$514.22	\$10.60
Middle	0.560	0.094	\$947.04	\$50.00
Upper	0.783	0.157	\$2,558.66	\$314.03

Notes: We winsorize the losses at the 90th percentile, which is why the expected losses do not monotonically increase relative to Table 2.

Table C2: Under-Diversification 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
Lower	0.388	0.019	\$1,159.08	\$8.46
Middle	0.560	0.035	\$2,619.98	\$51.65
Upper	0.783	0.048	\$7,374.92	\$277.25

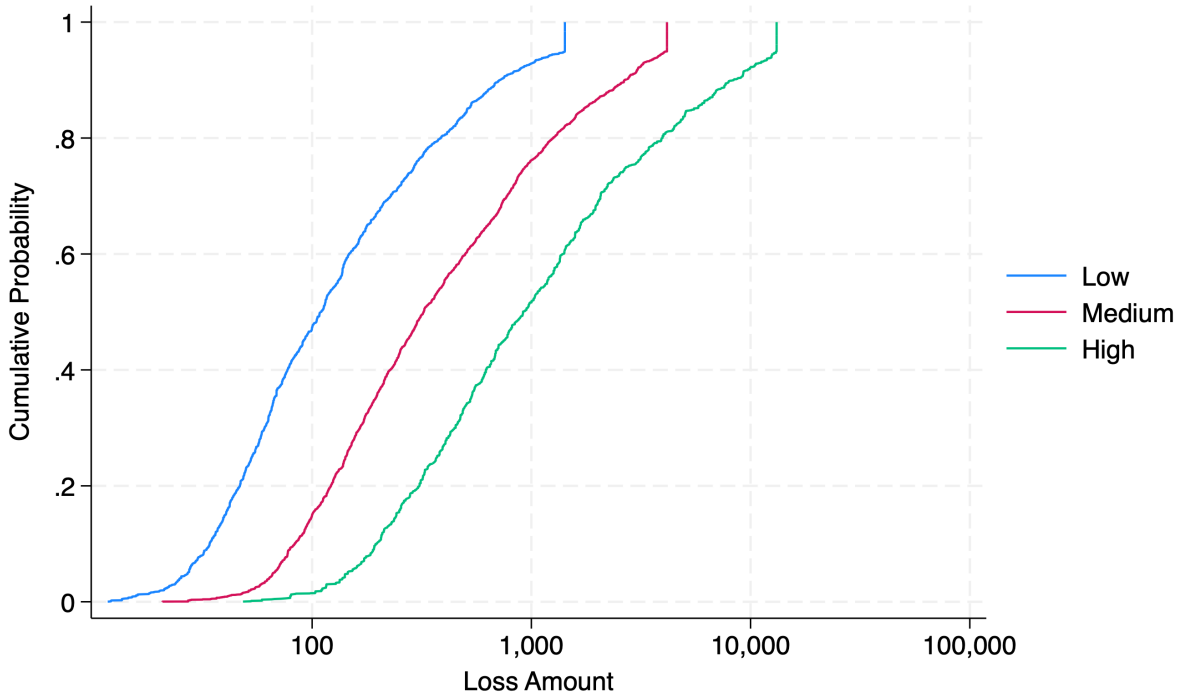
Notes: We winsorize the losses at the 90th percentile, which is why the expected losses do not monotonically increase relative to Table 2.

Table C3: Excessive Mutual Fund Fees Robustness Check: 20th Percentile of Fees

Income Group	s_j Share with Mutual Funds	f_j Share with Excessive Fees	L_j Average Loss Conditional on Excessive Fees	$s_j \cdot f_j \cdot L_j$ Expected Loss
Low Income (Bottom 25%)	0.187	1.000	$151.76	$28.39
Middle Income (Middle 25%-75%)	0.573	1.000	$245.54	$140.58
High Income (Top 25%)	0.819	1.000	$1,139.66	$933.94

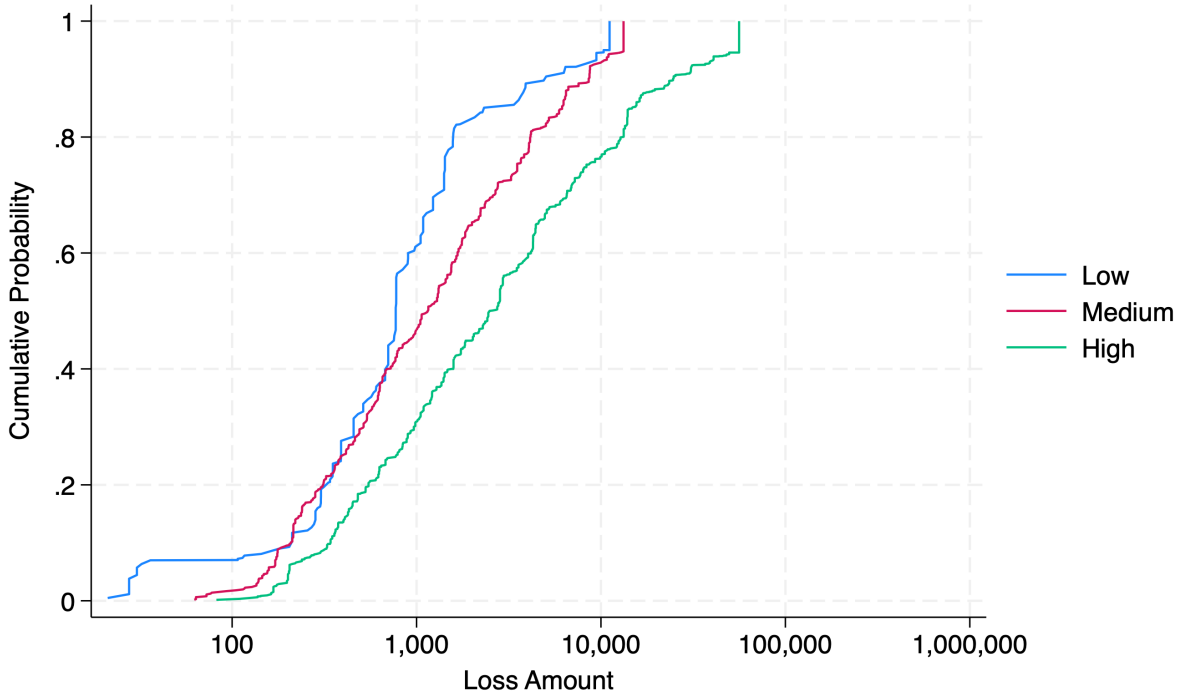
Notes: In this robustness check, we subtract the mean mutual fund fee from the 20th percentile, rather than from the 10th percentile as in Table 2.

Figure C1: CDF of Losses Due to Not Investing



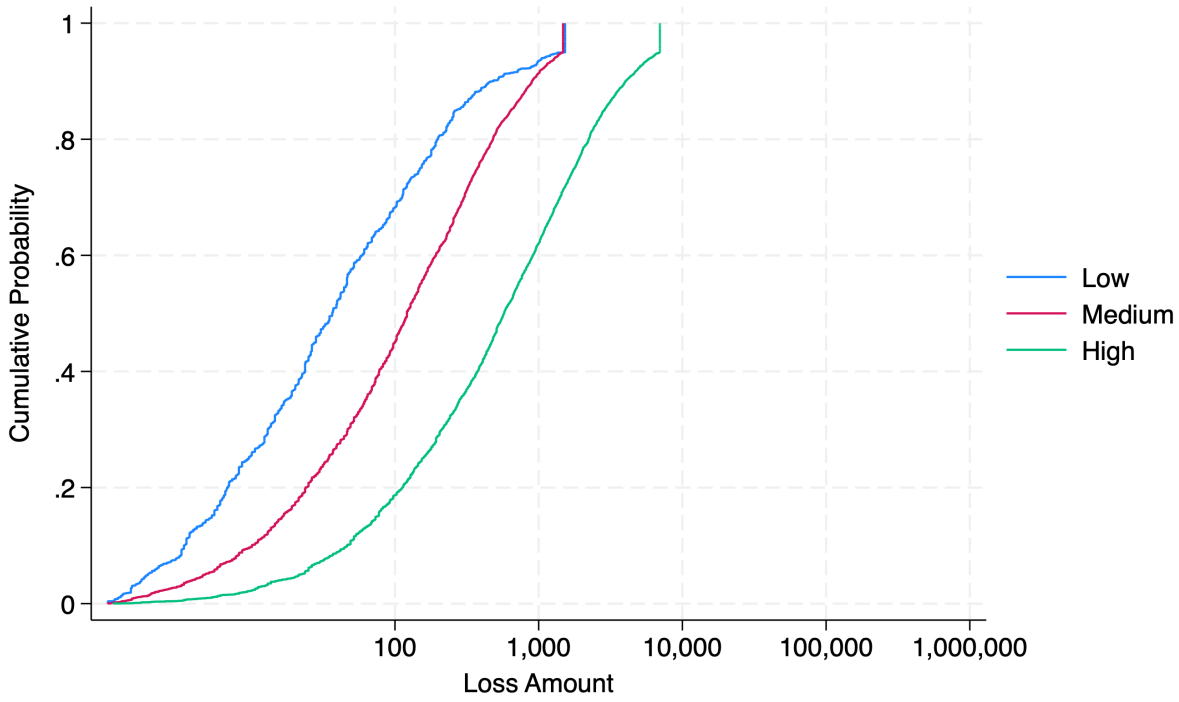
Notes: We plot the CDF of the annual losses due to not investing, winsorized at the 95th percentile.

Figure C2: CDF of Losses Due to Under-Diversification



Notes: We plot the CDF of the annual losses due to under-diversification, winsorized at the 95th percentile.

Figure C3: CDF of Losses Due to Excessive Mutual Fund Fees



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

Appendix D. Not Refinancing a Mortgage

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

$$-\sqrt{\frac{\sigma\kappa}{M(1-\tau)}\sqrt{2(\rho+\lambda)}}, \tag{38}$$

where σ is the standard deviation of the interest rate (estimated from historical mortgage interest rates); M is the mortgage size; κ 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); τ is the marginal tax rate faced by the household; ρ 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 λ 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 Γ is the number of years left in the mortgage).

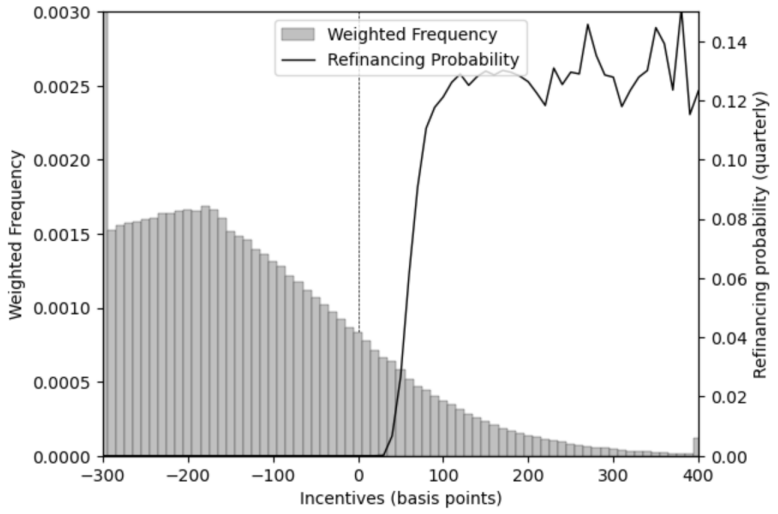
Robustness: Psychological Costs. This appendix presents robustness checks for our mortgage refinancing simulations, where we add in psychological costs similar to the Andersen et al. (2020) model. We add in psychological costs of refinancing on top of the Agarwal et al. (2013) minimum incentive to refinance, 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).

Table D1: Mortgage Refinancing with Psychological Costs

Income Group	s_j Share with a Mortgage	f_j Annual Probability of Not Checking for Refinancing Opportunities	L_j Average Loss Relative to Optimal Refinancing	$s_j \cdot f_j \cdot L_j$ Expected Loss
Low Income	0.159	0.686	$289.49	$50.06
Middle Income	0.400	0.573	$270.08	$107.06
High Income	0.549	0.547	$482.88	$244.56

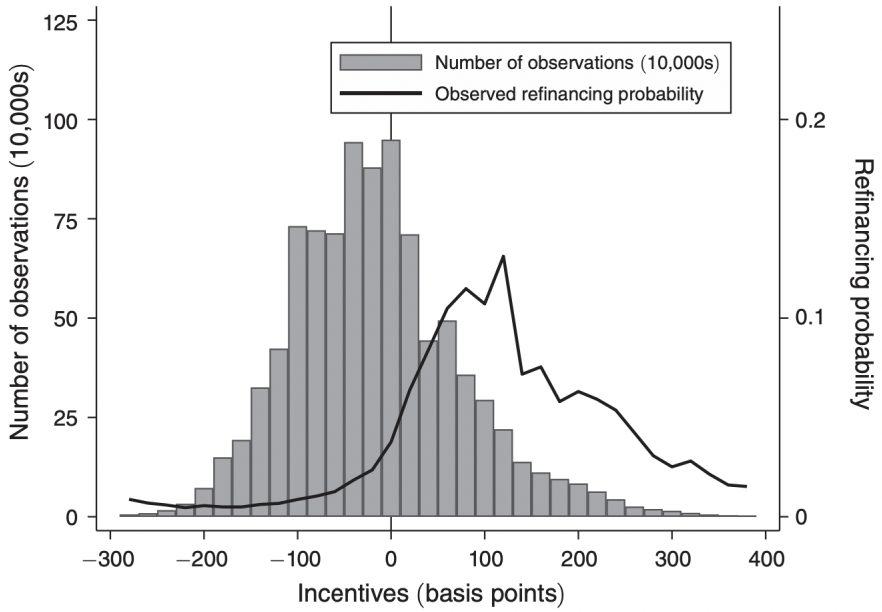
Notes: This robustness check includes psychological costs of refinancing, as determined from figure 9 of Andersen et al. (2020). f_j is modeled as an i.i.d. friction across the years, as opposed to assuming that a fixed fraction of individuals have a persistent friction.

Figure D1: Refinancing Incentives in Simulations, with Psychological Costs



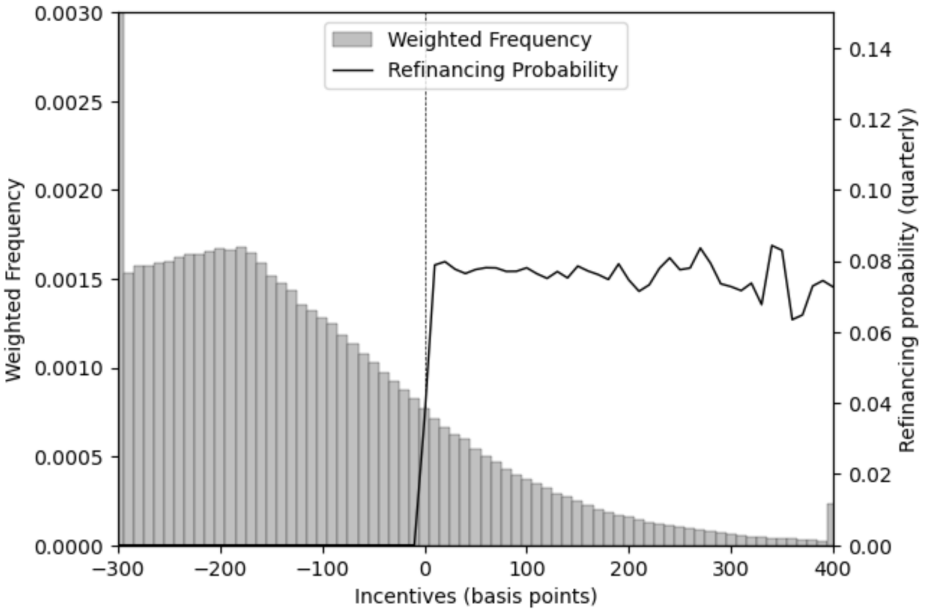
Notes: This robustness check includes psychological costs of refinancing, as determined from figure 9 of Andersen et al. (2020). The average mortgage in the plot above has 19.10 years left. The incentives on the x-axis are calculated after subtracting the optimal threshold for refinancing, so households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

Figure D2: 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.

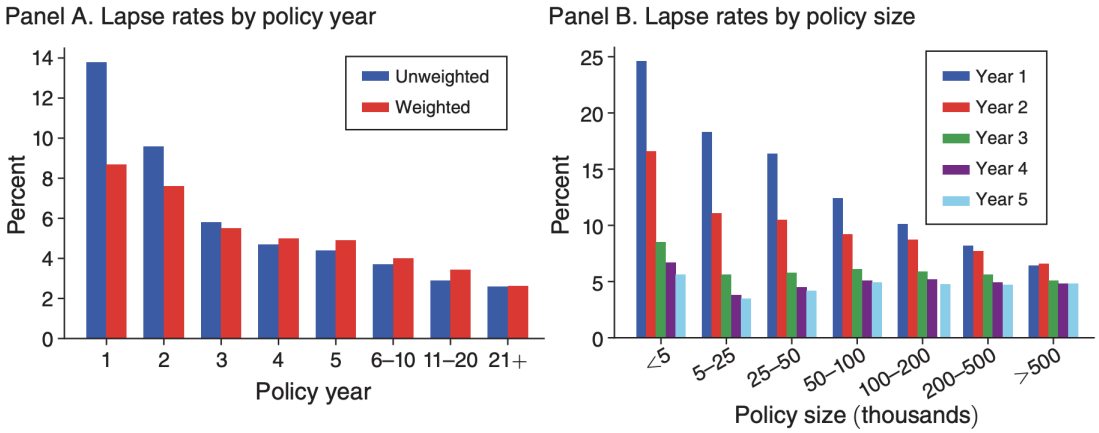
Figure D3: Refinancing Incentives in Simulations



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.

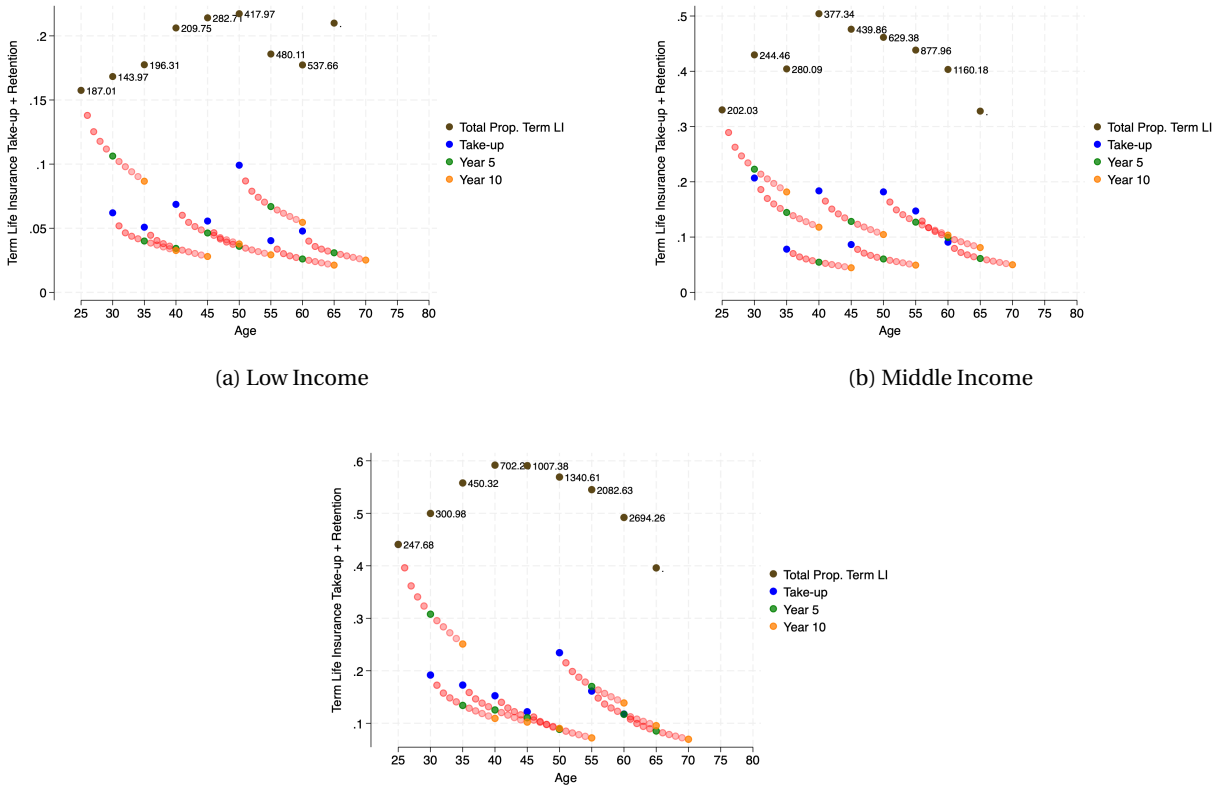
Appendix E. Suboptimally Lapsing Life Insurance

Figure E1: Lapsing Rate by Policy Size



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

Figure E2: TLI Purchase and Lapsing by Income Group



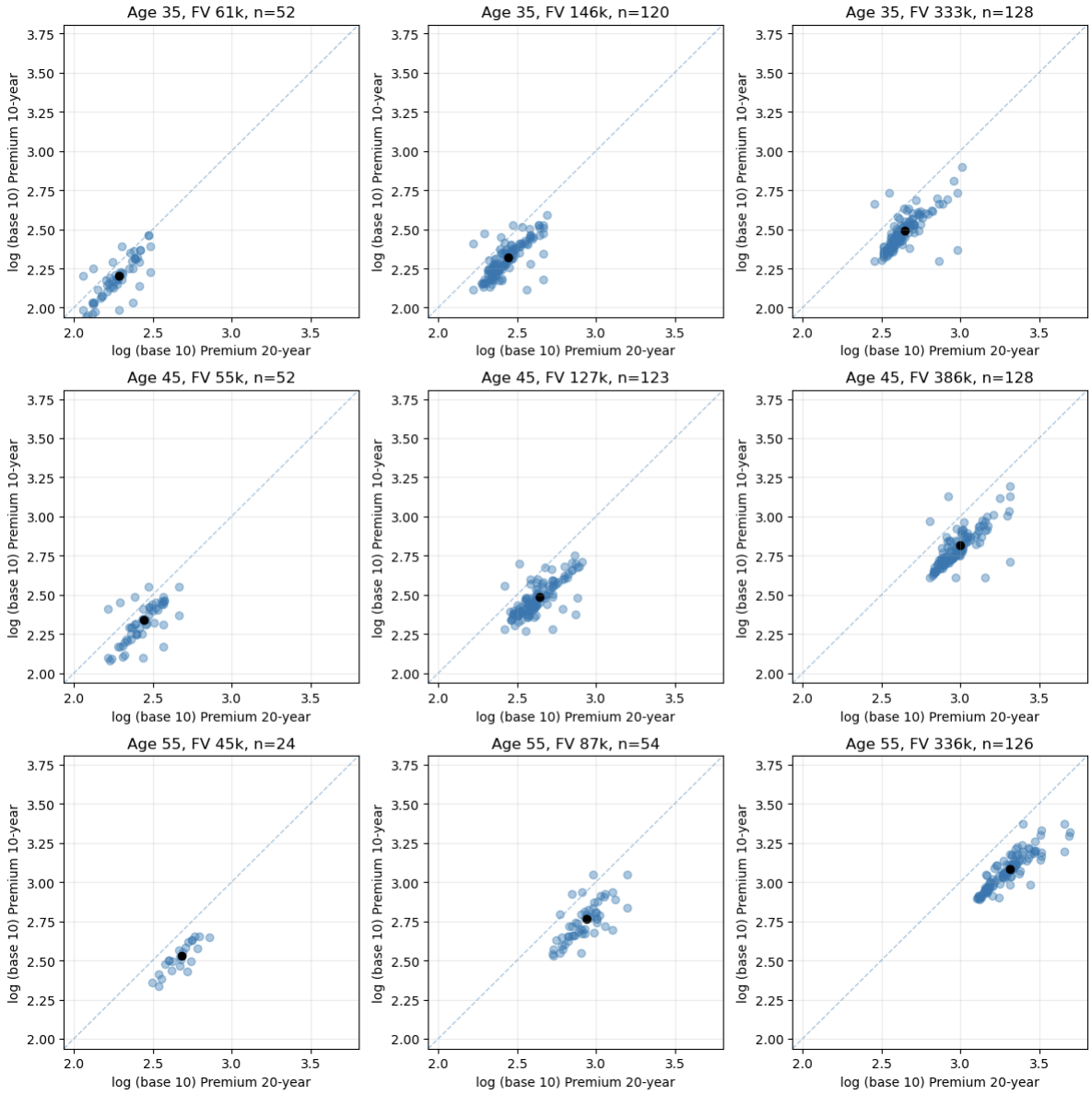
(a) Low Income

(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 E3: 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.

Table E1: Life Insurance Lapsing Parameters by Age and Income Group

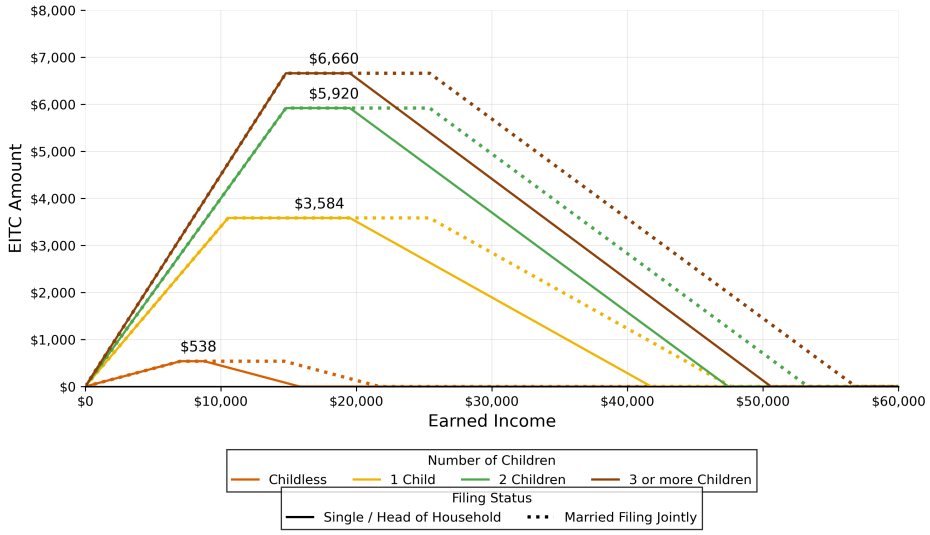
Income Group	Age	s_j	f_j	L_j
Low	25	0.1575	0.3252	10.75
Low	30	0.1683	0.2472	20.53
Low	35	0.1775	0.1347	19.59
Low	40	0.2062	0.1389	31.43
Low	45	0.2141	0.1320	42.59
Low	50	0.2173	0.1789	65.92
Low	55	0.1859	0.1434	124.79
Low	60	0.1773	0.1226	111.07
Middle	25	0.3302	0.3252	15.22
Middle	30	0.4297	0.2409	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.

Appendix F. EITC and SNAP

Table F1 showcases the FY 2020 SNAP cutoffs. We apply the standard deduction, earned income deduction, shelter deduction,[1] and healthcare and childcare deductions when computing the net income. 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).

Figure F1: 2020 EITC Cutoffs



Notes: We plot the 2020 EITC schedules, separately based on household filing status and number of children.

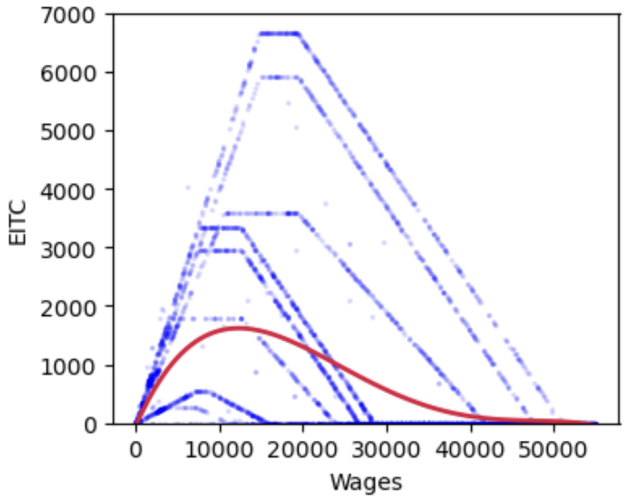
Table F1: Monthly SNAP Eligibility Cutoffs and Allotments for 48 States and D.C. (FY 2020)

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.

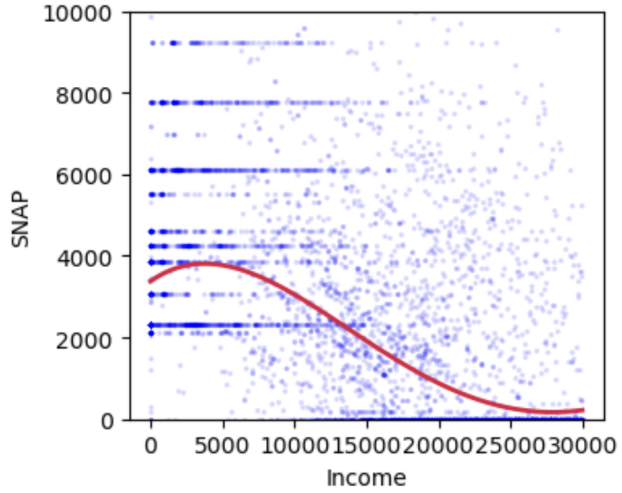
[1] We ignore the homeless shelter deduction since the PSID does not include homeless households in their sampling strategy.

Figure F2: PSID EITC for Ages 30–34



Notes: We plot the raw scatter points for labor wages versus amount of EITC available, as well as the polynomial line of best fit, using the 2011-19 PSID. While most scatter points follow the EITC schedule perfectly, some do not, primarily due the household earning business/other income along with labor income.

Figure F3: PSID SNAP for Ages 30–34



Notes: We plot the raw scatter points for labor wages versus amount of SNAP available, as well as the polynomial line of best fit, using the 2011-19 PSID.

Table F2: EITC Friction, Summary of Model Implementation

	Proportion Eligible (s)	Proportion Not Claiming (f)	Loss due to Not Claiming (L)	Expected Loss ($s * f * L$)
Low Income	0.942	0.200	\$842.96	\$158.79
Middle Income	0.391	0.200	\$641.58	\$50.22
High Income	0.137	0.200	\$671.40	\$18.40

Note: This table only shows data for households between 22 and 65 years old.

Table F3: SNAP Friction, Summary of Model Implementation

	Proportion Eligible (s)	Proportion Not Claiming (f)	Loss due to Not Claiming (L)	Expected Loss ($s * f * L$)
Low Income	0.930	0.180	\$2,183.49	\$365.59
Middle Income	0.296	0.180	\$1,036.83	\$55.24
High Income	0.102	0.180	\$1,159.62	\$21.27

Note: This table shows data for households of all ages.

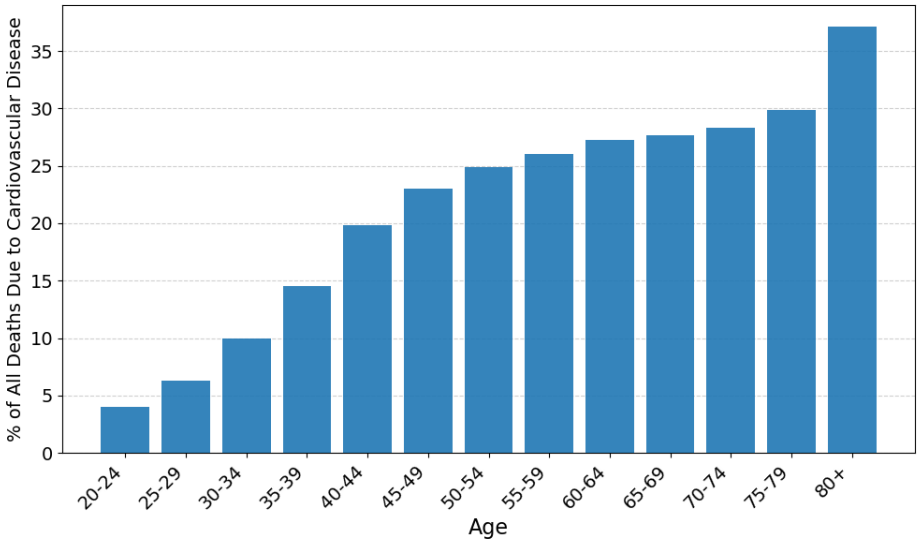
Appendix G. Health Frictions

Table G1: 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%
Average	**-32.0%**	**-36.5%**	**-22.3%**	**-24.5%**

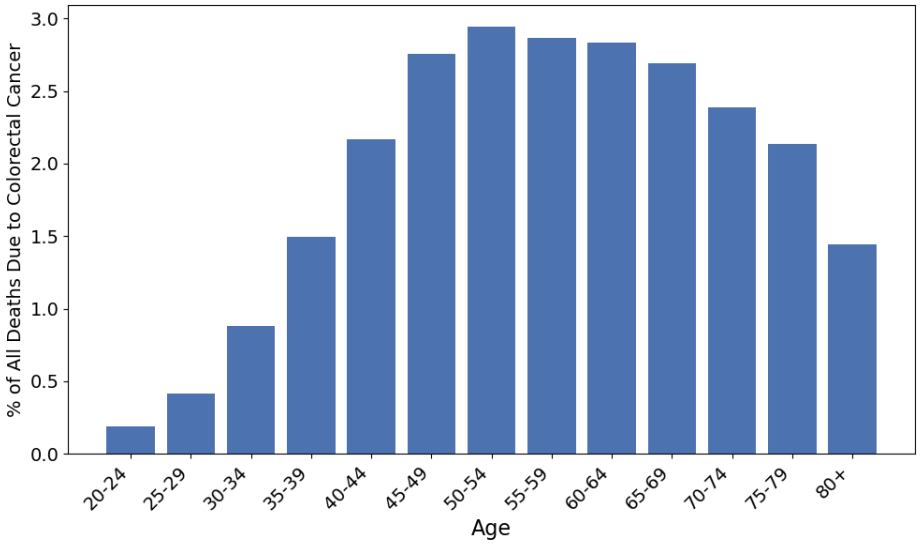
Notes: The studies AFCAPS/TexCAPS, WOSCOPS, CARE, and 4S do not report a first stage of compliance (or use ITT as TOT). For JUPITER, we use the estimate for overall mortality, as the impact on cardiovascular mortality is not reported. Averages are equal-weighted across all studies.

Figure G1: 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.

Figure G2: Percent of All Deaths Due to Colorectal Cancer from 2012–2020



Notes: Data from Centers for Disease Control and Prevention (2021).

Appendix H. Life Cycle Model

H.1 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:

$$V(\mathbf{x}_{it}, \mathbf{f}_i) = \begin{cases} U_B(W_{it}) & \text{if } a_{it} = a_T \\ \max_{S^L_{it}, S^X_{it}, \theta_{it}} \mathscr{B}(\mathbf{x}_{it}, \mathbf{f}_i, S^L_{it}, S^X_{it}, \theta_{it}) & \text{otherwise} \end{cases} \tag{39}$$

where the Bellman equation is:

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

subject to: (6)–(31) and

$$c_{it} + \big(S^L_{it} - L_{it}\big) + S^X_{it} = y_{it} + T_{it}$$

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

$$S^X_{it} \in [\underline{S}^X_{it}, \overline{S}^X_{it}]$$

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.

H.2 Additional Results

Table H1: Model Results: Lifetime Friction Impact (Levels)

Income Group	ΔTotal Income$_{lt}$	ΔConsumption$_{lt}$	ΔWealth$_{40}$	ΔWealth$_{65}$
Panel A: College Attendance				
Low	\$3,028	\$2,733	-\$21	\$472
Middle	\$10,325	\$12,122	\$1,027	\$3,333
High	\$4,966	\$6,408	\$691	\$2,255
Panel B: 2-Year For-Profit Attendance				
Low	\$4,883	\$5,616	\$368	\$802

Continued on next page

Table H1 – continued from previous page

Income Group	ΔTotal Income$_{lt}$	ΔConsumption$_{lt}$	ΔWealth$_{40}$	ΔWealth$_{65}$
Middle	\$10,825	\$13,178	\$893	\$3,729
High	\$4,164	\$5,329	\$427	\$1,883
Panel C: Stock Market Participation				
Low	-\$251	\$17,412	\$2,518	\$5,790
Middle	-\$1,108	\$84,703	\$11,094	\$36,357
High	-\$1,545	\$96,883	\$11,922	\$47,067
Panel D: Overdraft Fees				
Low	\$2,177	\$2,114	-\$82	-\$92
Middle	\$2,793	\$2,653	-\$289	-\$333
High	\$288	\$244	-\$67	-\$62
Panel E: Credit Card Late Fees				
Low	\$990	\$975	-\$30	-\$39
Middle	\$1,957	\$1,900	-\$206	-\$226
High	\$385	\$313	-\$70	-\$50
Panel F: Dominated Insurance Choice				
Low	\$3,481	\$3,567	-\$109	\$324
Middle	\$7,781	\$7,678	-\$830	\$1,070
High	\$5,527	\$5,329	-\$954	\$745
Panel G: Life Insurance Lapsation				
Low	-\$3	-\$5	\$1	\$0
Middle	\$84	\$84	-\$20	-\$0
High	\$1,300	\$1,080	-\$534	\$298
Panel H: Smoking				
Low	\$6,262	\$8,638	\$112	\$1,446
Middle	\$8,618	\$19,157	\$247	\$5,842
High	\$5,490	\$17,722	\$212	\$5,502

Notes: Each panel reports the average lifetime impact of removing a single friction, expressed in dollar levels. All variables with subscript lt denote undiscounted lifetime sums. ΔTotal Income$_{lt}$ is the change in the undiscounted lifetime sum of total income, as defined in (37). ΔConsumption$_{lt}$ is the change in the undiscounted lifetime sum of consumption. ΔWealth$_{40}$ and ΔWealth$_{65}$ are changes in total wealth (liquid plus 401(k) assets) at ages 40 and 65, respectively. Each entry is computed as the difference between the mean frictionless outcome and the mean baseline outcome within the income group. See Table 5 for the corresponding percent changes.

Table H2: Model Results: Per-Period Friction Impact

Income Group (j)	s_j	f_j	L_j	$s_j \cdot f_j \cdot L_j$
Panel A: College Attendance				
Low	0.478	0.204	$448	$44
Middle	0.236	0.204	$3,188	$153
High	0.061	0.204	$5,888	$73
Panel B: 2-Year For-Profit Attendance				
Low	0.070	1.000	$1,054	$73
Middle	0.044	1.000	$3,670	$161
High	0.010	1.000	$6,346	$62
Panel C: Stock Market Participation				
Low	1.000	0.180	-$20	-$4
Middle	1.000	0.160	-$101	-$16
High	1.000	0.080	-$276	-$22
Panel D: Overdraft Fees				
Low	1.000	0.304	$105	$32
Middle	1.000	0.281	$149	$42
High	1.000	0.047	$95	$4
Panel E: Credit Card Late Fees				
Low	1.000	0.323	$45	$15
Middle	1.000	0.305	$94	$29
High	1.000	0.051	$110	$6
Panel F: Dominated Insurance Choice				
Low	1.000	0.688	$75	$52
Middle	1.000	0.532	$218	$116
High	1.000	0.310	$265	$82
Panel G: Life Insurance Lapsation				
Low	1.000	0.181	-$0	-$0

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Table H2 – continued from previous page

Income Group (j)	s_j	f_j	L_j	$s_j \cdot f_j \cdot L_j$
Middle	1.000	0.172	\$7	\$1
High	1.000	0.149	\$130	\$19
Panel H: Smoking				
Low	1.000	0.237	\$394	\$93
Middle	1.000	0.150	\$866	\$130
High	1.000	0.075	\$1,109	\$83

Notes: Each panel reports the per-period friction impact for a single friction, with rows corresponding to permanent income groups. s_j is the probability of being subject to the friction in income group j. f_j is the probability of experiencing the friction conditional on being subject to it. L_j is the average per-period change in total income, as defined in (37), for friction-holders when the friction is removed, holding all other frictions at their baseline prevalence. $s_j \cdot f_j \cdot L_j$ is the expected per-period impact, equal to the product of the three preceding columns. The values of s_j and f_j reported here differ from the empirical estimates because they reflect how each friction is implemented in the model, mapped to model income groups via an OLS projection.