Consumer Credit with Over-Optimistic Borrowers*

Florian Exler Igor Livshits James MacGee Michèle Tertilt

February 1, 2022

Do cognitive biases call for regulation to limit the use of credit? We incorporate over-optimistic and rational borrowers into an incomplete markets model with consumer bankruptcy. Over-optimists face worse income risk but incorrectly believe they are rational. Thus, both types behave identically. Lenders price loans forming beliefs—type scores—about borrower types. This gives rise to a tractable theory of type scoring. As lenders cannot screen types, borrowers are partially pooled. Over-optimists face cross-subsidized interest rates but make financial mistakes: borrowing too much and defaulting too late. The induced welfare losses outweigh gains from cross-subsidization. We calibrate the model to the U.S. and quantitatively evaluate policies to address these frictions: financial literacy education, reducing default cost, increasing borrowing costs, and debt limits. While some policies lower debt and filings, only financial literacy education eliminates over-borrowing and improves welfare. Score-dependent borrowing limits can reduce financial mistakes but lower welfare.

Keywords: Consumer Credit, Over-Optimism, Financial Mistakes, Bankruptcy, Default, Financial Literacy, Financial Regulation, Type Score, Cross-Subsidization

JEL Classifications: E21, E49, G18, K35

---

*We thank Jason Allen, Christian Bayer, Russell Cooper, Dean Corbae, Marios Karabarbounis, Simas Kucinskas, José-Víctor Ríos-Rull, Juan Sanchez, Jeremy Tobacman, and audience members at many seminars and conferences for helpful comments and suggestions, and Jan Sun for excellent research assistance. We thank the Social Science and Humanities Research Council (Livshits, MacGee) and the German Research Foundation (through the CRC-TR-224 project A3 and the Gottfried Wilhelm Leibniz Prize, Tertilt) for financial support. The views expressed here are those of the authors and do not represent those of the Federal Reserve Bank of Philadelphia, the Federal Reserve System, or the Bank of Canada. Exler: Department of Economics, University of Vienna, Oskar-Morgenstern-Platz 1, A-1090 Vienna, Austria, florian.exler@univie.ac.at. Livshits: Research Department, Federal Reserve Bank of Philadelphia, Igor.Livshits@phil.frb.org. MacGee: Department of Economic and Financial Research, Bank of Canada, 234 Wellington Street, Ottawa, ON, K1A 0G9, Canada, JMacGee@bank-banque-canada.ca. Tertilt: Department of Economics, University of Mannheim, L7 3-5, D-68131 Mannheim, Germany, tertilt@uni-mannheim.de.

1 Introduction

The rise in consumer credit and personal bankruptcies has energized the debate over consumer financial protection. Much of this debate centers around whether borrowers' cognitive biases create a need for regulation to limit the misuse of credit (Bar-Gill and Warren 2008; Campbell 2016). Proponents of consumer finance regulations often argue that consumers overborrow due to behavioral biases, leaving some "trapped in debt."[1] Opponents meanwhile point towards the adverse effects arising from higher borrowing costs and reduced access to credit resulting from additional regulations (e.g., Zywicki (2013)). Although this debate is far from settled, the 2008 financial crisis helped crystallize support for regulatory reforms, such as the creation of the Consumer Financial Protection Bureau (CFPB) and the 2009 Credit Card Accountability Responsibility and Disclosure (CARD) Act.[2]

In this paper, we develop a novel framework with "rational" and "behavioral" consumers which we use to analyze consumer financial regulation. Given that much of the debate over regulation focuses on credit cards, our framework features unsecured credit and the option for consumers to default and not repay their debts. Specifically, we introduce over-optimistic borrowers into a standard incomplete markets economy with unsecured debt and equilibrium default (Chatterjee et al. 2007; Livshits, MacGee, and Tertilt 2007). In our life-cycle model, a borrower's type is not directly observable. Consequently, lenders price credit endogenously based on beliefs about a borrower's type, which are updated over a borrower's life.

The co-existence of over-optimistic and rational consumers allows us to study how the endogenous pricing of credit risk leads to spillovers from the borrowing and default decisions of different types. We show that over-optimists, who make mistakes in both their borrowing and default decisions, are cross-subsidized by rational borrowers. These mistakes suggest that regulation might improve welfare, which leads us to analyze several policies that target these mistakes. We find that even when these policies reduce mistakes, they are often not welfare improving.

We explore over-optimism about future income, rather than other specifications of behavioral consumers, for two reasons. First, this assumption gives rise

[1] See, for example, Dodd (CT) (2009).

[2] The CFPB regulates credit products and was part of the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act. The CARD Act limits credit card fees and increases disclosure requirements.

to a tractable model of type scoring and partial pooling of behavioral and non-behavioral consumers.[3] Second, substantial empirical work has documented that some consumers are over-optimistic about their future income (Arabsheibani et al. 2000; Dawson and Henley 2012; Balasuriya and Vasileva 2014; Balleer et al. 2021; Mueller, Spinnewijn, and Topa 2021; Mueller and Spinnewijn 2022).[4] Moreover, they generally underestimate the probability of experiencing negative events (Weinstein 1980; Puri and Robinson 2007). Motivated by these findings, we assume that behavioral consumers place too high (low) probabilities on positive (negative) transitory income shocks.[5]

Since we assume over-optimists believe they face the same risks as rational consumers, they differ from realists in being more prone to bad shocks *and* being unaware of the worse risks they face. While conceptually these are distinct features (and we decompose the contributions of each channel), in practice they often come hand in hand. We document that respondents in the Survey of Consumer Finances (SCF) with low financial literacy scores report being surprised by low income realizations more often (and have lower income on average) than individuals with high financial literacy. Relatedly, Balleer et al. (2021) document that US households are over-optimistic about their labor market prospects and that the extent of over-optimism is greater for the less educated. This pattern of being more exposed to shocks co-existing with over-optimism has also been documented for the self-employed. Despite facing more income risk than wage earners, the self-employed have been found to be more over-optimistic than the average population (Åstebro 2003; Arabsheibani et al. 2000).

Our model incorporates behavioral households in an incomplete market economy with bankruptcy populated by finitely lived heterogeneous agents subject to

[3]Our model equilibrium features pooling of over-optimistic and rational borrowers with identical observable characteristics. We use the term "partial pooling" to indicate that pooling takes place only within type-score bins so that there is no pooling across type-score bins.

[4]Dawson and Henley (2012) find 30% of British households to be over-optimistic about their future income. Balleer et al. (2021) use the New York Fed's Survey of Consumer Expectations to document that American workers are overly optimistic about the probability of finding (or losing) a job, with high school educated workers exhibiting a greater degree of over-optimism than the college educated. There is also evidence that over-optimists save less for retirement (Balasuriya and Vasileva 2014).

[5]An alternative interpretation is that they have limited financial literacy and do not fully understand their expected future financial position. While there is evidence pointing to the presence of non-sophisticated consumers, there is no consensus as to the frequency of either bias.

idiosyncratic earning shocks and stochastic expenditures (i.e., "expense shocks"). Households choose how much to borrow or save and whether to file for bankruptcy. There are two types of households: realists who hold correct beliefs about the uncertainty they face and over-optimists who believe they are realists (and, conditional on their state, behave as realists) but actually face systematically worse risk. If households do not default, then they can borrow or save in a one-period bond that is priced in a competitive debt market.

Financial intermediaries observe a household's earnings history, age and asset position, but they cannot directly observe whether a household is an over-optimist or a realist. Instead, financial intermediaries form beliefs—*type scores*—about the probability that a household is a realist. In equilibrium, lending interest rates depend on current income, age, the amount borrowed and the type score. This results in the endogenous pooling of over-optimists with realist borrowers who share the same type score. Since over-optimists believe they are realists, both types behave identically (conditional on their state) and there is no way for lenders to design screening contracts. As consumers age, lenders update their beliefs regarding a borrower's type based on observed realizations of their idiosyncratic uncertainty. The accuracy of type scores increases over the life-cycle. While borrowers do not update their beliefs about their type, they internalize how lender type-scores affect interest rates. The model thus provides a tractable theory of type scoring.

Over-optimistic consumers have higher levels of debt and default more often than rational consumers. Our decomposition shows that this is primarily driven by the incorrect beliefs of behavioral borrowers rather than by their worse income risk. These incorrect beliefs lead to mistakes by over-optimists who over-borrow and file too late compared to what an informed version of themselves would do. In our calibrated economy, if suddenly made aware, behavioral consumers would borrow 15% less and an additional 0.3% would file for bankruptcy. This arises because over-optimistic beliefs about future income encourage borrowers to postpone defaulting as they expect to repay their debt. Ex post, however, over-optimists are systematically surprised by lower income realizations, which sometimes leaves them unable to repay their debts.

These mistakes seemingly support the case for regulations to protect behavioral consumers. However, this conclusion ignores a mechanism working in favor of these consumers. In equilibrium, our model generates spillovers between rational and over-optimistic borrowers as the partial pooling of types gives rise to the cross-subsidization of interest rates. Since over-optimists default more often, cross-subsidization goes from rational to behavioral consumers. Regulation that reduces this cross-subsidization could thus hurt behavioral consumers.

To assess the implications of these forces for regulation, we analyze the welfare implications of several polices targeted at financial mistakes. First, we investigate the best case for financial literacy education: informing consumers about their true type. Second, we reduce default cost, inducing over-optimistic people to default earlier. Third, to target overborrowing, we make borrowing more costly via a proportional transactions tax.[6] Finally, we introduce a debt-to-income limit.

In the best-case scenario of financial literacy education, behavioral consumers completely avoid mistakes. This hypothetical literacy campaign provides a useful benchmark: when holding fixed lenders' type-scoring and pricing schedules—corresponding to a small-scale financial literacy intervention—eliminating financial mistakes leads to a substantial welfare gain for an over-optimist. However, if broad-based financial literacy education prompted lenders to update pricing, cross-subsidization would end and interest rates would become actuarially fair. Over-optimists' welfare gains drop by three-quarters, although rational consumers benefit from the breakdown of pooling. These experiments suggest that the estimated benefits from small-scale financial literacy experiments may exceed the benefits of large-scale programs, which sees lenders adjust their lending criteria.

Reducing default costs increases welfare for behavioral consumers and reduces their frequency of filing too late. However, since rational consumers benefit equally, these gains are not driven by fewer mistakes by over-optimists. Instead, in our calibrated model, overall default costs exceed their welfare maximizing level. We find that a tax on borrowing lowers the welfare of both types of consumers, although it does reduce the extent of over-borrowing and filing too late by behavioral consumers. Similarly, we find that introducing a cap on debt-to-income ratio results in lower welfare for both types of consumers. However, a debt-to-income cap succeeds in lowering the frequency of filing too late by over-optimists by nearly 90%.

Given the limited success of the above policies, we explore whether more-targeted policies can improve welfare. Since directly targeting behavioral people is impossible in our model, we analyze debt-to-income and debt-service ratio (DSR)

[6] Increased regulatory requirements are often cited as having a similar effect.

limits targeted at borrowers with a low type score (and a high probability of being behavioral). We find that such limits lower both borrowing and default, which are typically prime regulatory objectives. However, these policies still reduce welfare for both types, as the cost of restricting access to credit for some borrowers still exceeds the benefits. This suggests that metrics based on debt and default may provide a misleading guide to the effectiveness of credit market regulations.

Despite growing evidence pointing to the important role of behavioral biases in consumer finance, surprisingly little work has incorporated behavioral borrowers into quantitative models of consumer debt and default.[7] Three exceptions are Laibson, Tobacman, and Repetto (2000) and Nakajima (2012, 2017), who examine self-control problems; Laibson, Tobacman, and Repetto (2000) analyze hyperbolic discounters, while Nakajima (2012, 2017) explores "temptation preferences" based on Gul and Pesendorfer (2001). In addition to differing in the underlying nature of behavioral bias, Laibson, Tobacman, and Repetto (2000) and Nakajima (2012) consider economies populated solely by behavioral consumers and thus do not examine credit market spill-overs between behavioral and rational borrowers. Nakajima (2017) analyzes the implications of alternative bankruptcy rules for behavioral and rational consumers in a model without spillover effects where rational and behavioral consumers co-exist without any interaction. This differs from our environment where type scoring results in the partial pooling of types and the cross-subsidization of borrowing between rational and behavioral borrowers.[8]

A key contribution of this paper is to provide a tractable model of type scoring in consumer credit markets. Our approach circumvents the technical challenges of incorporating asymmetric information into the consumer credit scoring literature (Chatterjee, Corbae, and Ríos-Rull 2008; Chatterjee et al. 2020; Corbae and Glover 2018; Sanchez 2017; Elul and Gottardi 2015; Livshits, MacGee, and Tertilt 2016; Athreya, Tam, and Young 2012). To characterize equilibrium,

[7]Studies examining behavioral biases in consumer finance include Agarwal et al. (2015), who find that 40% of consumers do not choose the cheapest credit card contract, and Lander (2018), who argues that presence of non-strategic borrowers helps match the characteristics of bankruptcy filers. Calvert, Campbell, and Sodini (2007) find less financially sophisticated Swedish households to underinvest in higher return (but riskier) assets. Livshits (2020) surveys this literature.

[8]The extent to which the nature of behavioral bias matters for policy conclusions is an open question. For example, the impact of financial regulations on consumers with self-control problems may differ from what we find for over-optimism. We see this paper as a first step to quantitatively explore a plausible example of non-rational behavior for consumer credit markets with default.

Chatterjee et al. (2020) add unobservable extreme-value shocks to households' utility functions to introduce noise that renders perfect screening contracts impossible. Other authors assume that scores can only take two values (Athreya, Tam, and Young 2012), or rule out certain types of screening contracts (Sanchez 2017). By assuming behavioral and rational agents have the same beliefs (and thus preferences over available contracts), we provide a theory of type scoring *without* adverse selection. Our approach results in perfect "mimicking," as over-optimists make precisely the same choices as their rational peers (conditional on their observed state). This perfect "mimicking" implies that screening contracts are not effective. In addition, the pricing of credit over the life-cycle reflects a learning channel as lenders update their beliefs about a borrower's type. This allows us to tractably incorporate credit scoring into a quantitative life-cycle model of consumer credit. The pooling of borrowers (conditional on observables) implies that equilibria in our model yield the largest amount of cross-subsidization (within type-score bins).

Our work is also related to a theoretical literature that models behavioral consumers in credit markets (Heidhues and Koszegi 2010; Heidhues and Koszegi 2015; Eliaz and Spiegler 2006). Several papers show that behavioral (and naive) debtors can sometimes pay more for the same product than (informed) rational debtors. For example, Heidhues and Koszegi (2015) argue that lenders can take advantage of borrowers who underestimate their future impatience by backloading repayments and penalties these borrowers do not anticipate paying ex-ante. Unlike our paper, these works do not incorporate default. This is important since risk-based pricing is often cited as justifying higher pricing for some consumers and because high default rates are a major concern in the policy debate. We show that the option of default leads to a natural form of cross-subsidization that benefits behavioral consumers, which is absent in models without default.[9] Our finding that over-optimistic borrowers may be cross-subsidized is similar in spirit to that of Sandroni and Squintani (2007), who examine insurance markets with rational and over-confident agents. Unlike Sandroni and Squintani (2007) who focus on how the presence of over-confident agents impacts adverse selection between rational high- and low-risk types, our model abstracts from adverse selection. This allows

[9]Bond, Musto, and Yilmaz (2009) define a *predatory loan* as one that a borrower would decline if they had the same information as the lender. Contrary to Bond, Musto, and Yilmaz, however, even if one were to correct their incorrect beliefs, over-optimists would continue to choose their loan contracts due to the cross-subsidization from rational types.

us to quantitatively assess the pattern of cross-subsidization between low-risk rational borrowers and over-optimists over the life-cycle.

The remainder of the paper is organized as follows. We describe our model in Section 2 and our calibration in Section 3. Section 4 reports the main quantitative results on how type scores evolve and how over-optimists affect credit markets. Section 5 analyzes the impact of several regulatory policies. In Section 6, we consider type-score dependent policies. Section 7 concludes.

2 Model Environment

The model incorporates behavioral consumers and type scoring by lenders into an otherwise standard incomplete-markets heterogeneous-agent life-cycle economy with defaultable one-period debt. The economy is populated by measure 1 of J-period lived consumers who face idiosyncratic income and expense shocks. A fraction λ of households are behavioral and have over-optimistic beliefs about the idiosyncratic uncertainty they face, while $(1-\lambda)$ have realistic (correct) beliefs. We assume behavioral consumers face worse transitory income risk but incorrectly believe that they face the same risk as realists.[10] Consequently, both types of consumers have identical beliefs about the distribution of transitory income shocks.

We examine a small open economy where the risk-free interest rate is exogenous.[11] Markets are incomplete as the only financial instruments are one-period bonds. Default makes debt partially state-contingent. Debt is priced endogenously by competitive lenders who observe the history of consumers' income and expense shocks. While lenders know the fraction of over-optimists, λ, they cannot directly observe a consumer's type. Thus, lenders form beliefs about borrowers' types, which we term *type scores* and update these beliefs each period, based on consumers' realized income shocks. The bond-price schedule offered to a consumer reflects the expected default risk and, thus, depends on the type score.

At the beginning of each period, income and expense shocks realize. Lenders observe these realizations and update type scores. Then, consumers decide whether

[10] In an earlier version, we examined the case where over-optimists held incorrect beliefs about transitory expense shocks. Our preliminary results indicated that many of the implications are qualitatively similar to those reported in this paper for transitory income risk over-optimism.

[11] This paper focuses on unsecured debt, which comprises a small share of the overall financial market. This suggests changes in debt to have little effect on the risk-free rate of return.

to file for bankruptcy and, if they do not file, how much to borrow or save.

2.1 Households

Consumers maximize their expected discounted lifetime utility,

$$\mathbb{E}^T \sum_{j=1}^{J} \beta^{j-1} \left[u\left(\frac{c_j}{n_j}\right) - \delta_j \chi \right], \tag{1}$$

where β denotes the discount factor, the sequence of consumption levels $\{c_j\}_{j=1}^J$ is adjusted by household size n_j, δ_j is the indicator of filing for bankruptcy at age j, and χ is a utility cost of bankruptcy. $T \in \{R, B\}$ denotes a household's type: rational (R) or behavioral (B). Behavioral consumers have over-optimistic expectations $\mathbb{E}^B$, which influence their consumption-savings choice and their default choice.

Households face idiosyncratic expense shocks $\kappa \geq 0$, drawn from a finite set $K = \{0, \kappa_1, ..., \kappa_N\}$ with corresponding probabilities $\{\pi_0, ...\pi_N\}$. These shocks capture unforeseen expenses such as medical bills and costs of family disruptions. An expense shock directly changes the net asset position. Expense shocks are independently and identically distributed and are independent of income shocks.

Unless an age-j household files for bankruptcy, it choses its consumption and debt (asset) level for the next period. The household also faces a menu of debt prices (interest rates) $q(\cdot)$ that reflects its future default risk and is a function of how much it chooses to borrow. The budget constraint is

$$c_j + d_j + \kappa \leqslant y_j^T + q(d_{j+1}, z, j, s) d_{j+1}, \tag{2}$$

where c_j is consumption, d_j is the current outstanding debt (or savings, if $d < 0$), κ is the realized expense shock, y_j^T is their current income, and d_{j+1} is the debt they promise to repay next period (amount of defaultable bonds the household sells to lenders). If the household is saving, the bond price is simply $q^s = \frac{1}{1+r^s}$. For a borrower, the bond price q^b is a function of the debt level d_{j+1}, the current realization z of the persistent income shock, the household's age j, and its "type score" s, which is the lenders' likelihood that the household is type R (see Equations (7) and (8) for details). The budget constraint in bankruptcy is described in Section 2.1.2.

Labor income is the product of a deterministic life-cycle component and idiosyncratic productivity shocks:

$$y_j^T = e_j z_j \eta_j^T, \tag{3}$$

where e_j is the life-cycle component, z_j is a persistent autoregressive earnings shock characterized by $\ln z_j = \rho \ln z_{j-1} + \varepsilon_j$ with $\varepsilon_j \sim N(0, \sigma_\varepsilon^2)$, and η_j^T is a transitory earnings shock that is drawn from type T dependent distributions.

2.1.1 Rational and Behavioral Consumers

Rational and behavioral consumers differ along two dimensions. First, consumers differ in the transitory income risks they face. Behavioral agents face more downside risk, that is a higher probability of low realizations of the transitory income shock η. Second, behavioral agents are not aware of their worse income risk, as they believe they face the same distribution of transitory income shocks η as realists. Formally, we assume that all consumers have a dogmatic prior that they face the same (good) income shock process. Hence, behavioral consumers are over-optimistic about their transitory income risk.[12]

This model specification of over-optimism is essential for making the model analytically tractable. Since behavioral agents are convinced they are realists, they will make the same decision as a rational agent in any given state. Thus, there is no way for a lender to separate ("screen") types.[13]

Realists, on the other hand, have rational beliefs about their income risk. Their beliefs coincide with the true distribution of the transitory income shocks they face.

$$\mathbb{E}(\eta^B) < \mathbb{E}^B(\eta^B) = \mathbb{E}^R(\eta^R) = \mathbb{E}(\eta^R), \tag{4}$$

where $\mathbb{E}$ is the true mean and $\mathbb{E}^T$ denotes the subjective expectation of type T.

[12] As we discussed in the Introduction, this is consistent with our empirical analysis using the SCF and the findings in (Balleer et al. 2021).

[13] Behavioral consumers have a dogmatic prior and do not update their beliefs as they age. They interpret bad transitory income realizations as bad luck, which can also befall rational agents. However, they understand that lenders use all available information to update their beliefs (type scores). Abstracting from learning is consistent with Mueller and Spinnewijn (2022) who document that the unemployed are over-optimistic about job finding rates and do not update their beliefs as they remain unemployed.

2.1.2 Bankruptcy

Consumers can file for bankruptcy. As in Chapter 7 in the U.S., a bankruptcy filing discharges the household's debt so a filer enters the following period with zero debt (unless hit with an expense shock that period).[14] Individuals cannot file for bankruptcy in consecutive three-year periods, which captures the six-year exclusion after a Chapter 7 bankruptcy. Furthermore, filers must repay a fraction γ of their income upon bankruptcy.[15] As filers cannot save or borrow, filers consume their income net of garnishment. The budget constraint in bankruptcy is

$$c_j = (1-\gamma)y_j^T. \tag{5}$$

In addition to the financial cost γy_j^T, filers incur a utility cost χ that captures other costs (e.g., the "stigma") associated with bankruptcy. After a bankruptcy, creditors have no claims on a filer's future income or assets, as is the case after a Chapter 7 filing.

2.2 Financial Intermediaries

Financial intermediaries are competitive and can borrow and save at the exogenous risk-free rate, r^s. When extending loans to households, they incur a proportional transaction cost, τ. Lenders offer each borrower a personalized bond-price schedule, which depends on the face value to be repaid next period, d'. Intermediaries take into account expected losses from default when determining this schedule, $q(d', \cdot)$. It depends on the borrower's age, j, current realization of the persistent income state, z, the amount borrowed, d', and the lenders' perception of the borrower's type, T. The latter is summarized by a *type score*, s.[16]

Type scores represent the probabilities that intermediaries attach to a household being rational. Although intermediaries cannot directly observe a house-

[14] Chapter 7 constitutes roughly 70% of filings in the U.S. and we abstract from Chapter 13. See Mecham (2004) for an in-depth description of U.S. bankruptcy law.

[15] This represents filing costs and the good faith effort required from borrowers to repay their debt. Total filing costs comprise court and legal fees, see Sullivan, Warren, and Westbrook (2000).

[16] The current realization of persistent income, z, is informative about future income and thus predictive of future default risk. Transitory income, η, and the expense shock, κ, are idiosyncratic and not directly informative of future default risk. In standard models, loan prices do not depend on their realizations. However, in our model, the realizations of η are informative about the borrower's underlying type and thus affect prices through the type score.

hold's type (i.e., realist or behavioral), they can observe the history of the household's realizations of transitory income shocks, η. Type score s thus summarizes the lenders' posterior belief of a borrower's type. Type scores are updated using Bayes' rule. All households enter the economy with the informed prior $s_0 = 1 - \lambda$. At the beginning of each period, after shocks are realized, the type score is updated using the prior s_{-1} and the shock realizations η to update:

$$s(\eta, s_{-1}) = \frac{s_{-1}\text{Prob}^R(\eta)}{s_{-1}\text{Prob}^R(\eta) + (1 - s_{-1})\text{Prob}^B(\eta)}. \tag{6}$$

Since over-optimistic households do not learn their own type and believe they face the same risks as realists, households' choices do not convey any additional information about a household's type. The decision rules of an over-optimistic consumer, conditional on the state (which includes the type score) and bond price, are the same as those of a rational household.

Conditional on the probability that a household is rational (s) and on the household's age (j) and persistent income realization (z), intermediaries accurately forecast the borrower's default probability, $\theta(d', z, j, s)$ for each face value (d'), and price the loan accordingly.

2.3 Equilibrium

Perfect competition and free entry result in lenders earning zero expected profits on each loan. Conditional on observable characteristics (persistent income z and age j) and a household's type score (s), bond-price schedules are determined by the default probability of a household $\theta(d', z, j, s)$ and the risk-free rate. Upon defaults, banks recover a fraction $\gamma y/(d' + \kappa')$ of the loan's face value through garnishment, which is proportionally allocated to outstanding loans and unpaid expenses.

The zero profit condition implies a bond-price schedule of

$$q^{ub}(d', z, j, s) = (1 - \theta(d', z, j, s))\overline{q} + \theta(d', z, j, s)E\left(\frac{\gamma y}{d' + \kappa'}\right)\overline{q}, \tag{7}$$

where $\overline{q} = \frac{1}{1+r^s+\tau}$ is the price of risk-free debt. q^{ub} is the expected repayment next period discounted by the risk-free borrowing interest rate. We further introduce an interest rate cap $\overline{r}$, which can be thought of as a usury law. Loans that carry interest rates above this cap are banned by setting their bond price to zero. This yields the equilibrium loan price

$$q^b(d', z, j, s) = \begin{cases} q^{ub}(d', z, j, s) & \text{if } q^{ub}(d', z, j, s) \geqslant \frac{1}{1+\bar{r}} \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

Consumers take the equilibrium bond-price schedule as given, as well as how lenders update type scores and interest rates following transitory income shock realizations.[17] The households' optimization problem is summarized by a value function V, which is the value of not defaulting, while $\overline{V}$ is the value of filing for bankruptcy. Since bankruptcy cannot be declared in consecutive periods, we define the value of delinquency, $\tilde{V}$, for households ineligible for bankruptcy.[18] In delinquency, the same fraction of income is garnisheed as in bankruptcy and the debt is rolled over at a fixed interest rate r^r. All value functions depend on whether beliefs are rational or over-optimistic, $T \in \{R, B\}$:

$$\begin{aligned} V_j^T(d, z, \eta, \kappa, s) = & \max_{c,d'} \left[u\left(\frac{c}{n_j}\right) + \beta \mathbb{E}^T \max\left\{ V_{j+1}^T(d', z', \eta', \kappa', s'), \overline{V}_{j+1}^T(z', \eta', s') \right\} \right] \\ & \text{s.t. } c + d + \kappa \leqslant y_j^T + q(d', z, j, s) d' \end{aligned} \tag{9}$$

$$\begin{aligned} \overline{V}_j^T(z, \eta, s) = \; & u\left(\frac{c}{n_j}\right) - \chi + \beta \mathbb{E}^T \max\left\{ V_{j+1}^T(0, z', \eta', \kappa', s'), \tilde{V}_{j+1}^T(z', \eta', \kappa', s') \right\} \\ & \text{s.t. } c = (1-\gamma) y_j^T \end{aligned} \tag{10}$$

$$\begin{aligned} \tilde{V}_j^T(z, \eta, \kappa, s) = \; & u\left(\frac{c}{n_j}\right) - \chi + \beta \mathbb{E}^T \max\left\{ V_{j+1}^T(d', z', \eta', \kappa', s'), \overline{V}_{j+1}^T(z', \eta', s') \right\} \\ & \text{s.t. } c = (1-\gamma) y_j^T, \qquad d' = (\kappa - \gamma y_j^T)(1 + r^r). \end{aligned} \tag{11}$$

An equilibrium is a set of value functions, optimal decision rules for consump-

[17]All consumers are aware that part of the population is over-optimistic, but all consumers believe they do not belong to that group.

[18]Our notion of delinquency addresses the possibility of empty budget sets for a consumer who is ineligible for bankruptcy but draws a large expense shock. The only debt in this case is the expense shock. Since delinquency is both unattractive (entailing all the costs of bankruptcy without the benefit of discharging debt) and the likelihood of a large expense shock is low, only 0.4% of bankruptcy filers transition to delinquency in our benchmark calibration. This is fewer than the number impacted by the large expense shock. Delinquency in our model is thus quite different from the more common use of delinquency to refer to being a few months late on a payment.

tion $c(\cdot)$, debt levels $d'(\cdot)$ and default, default probabilities $\theta(\cdot)$, and bond prices $q^b(\cdot)$, such that households optimize (equations (9)-(11)), and bond prices are such that intermediaries earn zero profits (equation (7) holds), taking the default probabilities as given. The model is solved numerically by backwards induction.

2.4 Welfare Measures

Since behavioral agents' beliefs are incorrect, their expected utility at birth differs from the assessment of a planner (or of a behavioral agent if made aware of the true income process). Since over-optimists overestimate (underestimate) positive (negative) outcomes, their average expected consumption exceeds the average realized consumption of behavioral individuals.

To evaluate the "true" welfare of behavioral agents, we introduce a welfare measure that is not distorted by biased expectations. We define the paternalistic welfare of a newborn behavioral agent W^P as the utility behavioral agents would expect if they used correct rational expectations but still behaved ignorantly:

$$W^P = \mathbb{E} \sum_{j=1}^{J} \beta^{j-1} \left[u\left(\frac{c_j}{n_j}\right) - \delta_j \chi \right], \tag{12}$$

where $\{c_j\}_{j=i}^J$ is the sequence of consumption realizations induced by the optimal decision rules for consumption, debt, and default under over-optimistic beliefs of type B. These policies solve the behavioral agent's problem in equations (9)—(11).

2.5 Theoretical Insights

Our model yields two interesting qualitative insights. First, in equilibrium rational borrowers generally face higher than actuarily fair interest rates. As a result, rational borrowers cross-subsidize behavioral borrowers. This pattern of cross-subsidization is the opposite of that found in much of the literature (see, e.g., Heidhues and Koszegi (2010)).

Cross-subsidization in our model is driven by the combination of the partial pooling of types and behavioral borrowers having higher default rates. The higher default rates of behavioral borrowers are due to their facing a higher probability of adverse income shocks than rational borrowers. Since adverse shocks increase the probability of bankruptcy, behavioral borrowers generally default more often than rational agents. Despite these differences in default risk, our assumption that both types have identical beliefs about their income processes implies that lenders cannot design a separating contract. As a result, rather than being exploited by lenders, behavioral agents benefit from cross-subsidized borrowing interest rates.

The pooling of borrowers (conditional on observables) implies that equilibria in our model yield the largest amount of cross-subsidization (within type-score bins). Our assumption that behavioral and rational agents have the same beliefs (and thus preferences over available contracts) eliminates adverse selection and results in perfect "mimicking," as over-optimists make precisely the same choices as their rational peers (conditional on their observed state).

The second qualitative insight is that transitory income shocks can have long-lasting effects on access to credit. Transitory income shocks can affect borrowers' type scores and thereby their current and future interest rate schedules. Thus, the presence of behavioral agents can affect rational borrowers beyond the cost of cross-subsidization, as adverse transitive income shocks can trigger a downgrade of a borrower's type score, making borrowing more expensive. These downgrades also coincide with periods of high desire to borrow to smooth consumption after an adverse income shock. Thus, the mechanism highlighted in Athreya, Tam, and Young (2009) for persistent shocks is present in our model for transitory income shocks due to multiple types and type-score updating.

3 Benchmark Calibration

Since much of the policy discussion surrounding behavioral consumers and consumer financial protection is recent, our benchmark calibration targets aggregate data over the period 2013-2017.[19] We also use the SCF from 2016. Our calibration proceeds in two steps. First, several parameters are set externally, including those that have a clear data counterpart. Second, we calibrate the remaining parameters internally to match several data moments.

[19]We use a five-year average of the data to smooth year-to-year fluctuations.

3.1 Externally Calibrated Parameters

Consumers enter the economy at age 20 and live for 54 years over 18 three-year periods. For the first 15 periods, consumers earn stochastic (labor) income. During the last three periods, consumers receive non-stochastic retirement benefits. The felicity function is $u(c) = \frac{(c/n_j)^{1-\sigma}-1}{1-\sigma}$. We set the coefficient of relative risk aversion to $\sigma = 2$. For n_j we use the household size life-cycle profile in equivalence scale units from Livshits, MacGee, and Tertilt (2007).[20]

We follow Livshits, MacGee, and Tertilt (2007) in parameterizing the expense shocks to U.S. estimates of medical expenses, divorces, and unplanned parenthood.[21] The support of expense shocks, K, has three elements: $\kappa \in K = \{0, \kappa_1, \kappa_2\}$. The smaller shock is 26.4% of average three-year income. The large shock corresponds to 82.18% of the average three-year income. The probabilities $[\pi_1, \pi_2]$ of these shocks realizing are 7.1% and 0.46%, respectively. Expense shocks are assumed to hit only working-age households.

Labor earnings include a persistent and a transitory component (see Equation (3)). While there are many empirical estimates that decompose income into such a process, we need two transitory shock processes—one for behavioral and one for rational people. There is no obvious way of estimating these processes separately since the different types are unobservable, even to the agents in our model. Instead, we target an average income process from the literature (specifically we use the process from Livshits, MacGee, and Tertilt (2010)) and then split the transitory component into two processes as explained below.[22]

We represent the persistent shock as a five-state Markov process. The parameters of this process map into an auto-correlation of $\rho = 0.95$ and a variance of innovation $\sigma_\varepsilon^2 = 0.025$. The transitory shock can take three values: $\eta \in [\eta_1, \eta_2, \eta_3]$. On average (including behaviorals and rationals), 10% of households receive a low

[20]See Livshits, MacGee, and Tertilt (2003) for the profile. We also constructed more life-cycle profiles from recent U.S. Census Bureau data and found little change in the last three decades.

[21]Note that the original expense-shock process was based on data on medical expenses, unwanted births, and divorces from the mid-1990s. However, these numbers remained stable over the last three decades: Medical out-of-pocket spending remained stable as a fraction of median household income. The number of births per 15-44 year-old women also was stable. The number of unwanted births slightly increased but divorces per 1,000 population declined slightly.

[22]Our income process is consistent with Storesletten, Telmer, and Yaron (2004), Hubbard, Skinner, and Zeldes (1994), and Carroll and Samwick (1997). We map annual values into triennial values and employ the Tauchen method (cf. Adda and Cooper (2003)) to discretize income shocks.

or high transitory income shock each period. The support is set to match the variance $\sigma_\eta^2 = 0.05$ with a mean of 1. Retirees receive a deterministic pension of 20% of the average income in the economy, plus 35% of their final persistent income.

Over-Optimism

Our calibration strategy targets two parameters related to behavioral agents: the fraction of behavioral agents in the population, λ, and their degree of over-optimism (defined below). We use data from the 2016 SCF to pin down these parameters.

We set the fraction of behavioral agents, λ, to the share of SCF respondents with low financial literacy. Specifically, we classify as behavioral households those that correctly answer at most one out of three simple financial literacy questions. This yields a fraction of behaviorals of $\lambda = 17\%$. See Appendix A for further details.

By assumption, over-optimists differ from rational people only in the transitory income process. Our calibration further assumes they face the same shock magnitudes η_1, η_2, η_3 and differ only in the probabilities. We define the degree of over-optimism as the ratio of the probability of a low transitory income realization of the two types of agents: $\text{Prob}^B(\eta_1)/\text{Prob}^R(\eta_1)$ and call this ratio ψ.

To pin down ψ, we use a question in the SCF that asks consumers whether their income is higher, lower, or the same as that of a usual year. Consistent with our model of over-optimism, significantly more households report their income is lower than usual rather than higher (see Table A2).[23] Respondents we classify as behavioral (because of their low score on the financial literacy questions) are 1.36 times more likely to report a "lower than usual" income. Thus, we set $\psi = 1.36$. Given ψ, λ and the overall transitory income process discussed above, it is then straightforward to derive the shock probabilities for rational and behavioral people (see Table 1, and Appendix A for further details).

Our modelling assumptions imply that behavioral people not only have incorrect beliefs but also experience negative (positive) income shocks more (less) often. This pattern is reflected in the SCF: respondents we classify as behavioral due to their low financial literacy report more negative and fewer positive surprises about their income (see Table A2). Furthermore, the negative correlation between being behavioral and expected income implies that low literacy respondents in the SCF

[23] Although we report the responses to this question for the 2016 SCF, this pattern holds across survey years.

Table 1: Transitory Income Shock Process

Probabilities:		η_1	η_2	η_3
Overall	Prob(η)	10%	80%	10%
Rational	Prob$^R(\eta)$	9.43%	80%	10.57%
Behavioral	Prob$^B(\eta)$	12.79%	80%	7.21%
Magnitudes:		0.59	0.98	1.57

should have lower average income. This is a testable assumption. Indeed, we find that financial literacy is highly correlated with income and education in the SCF. See Table A1 in Appendix A for details.

3.2 Financial Market

We set the safe interest rate to $r^s = 1\%$ annually.[24] To pin down the lending transaction cost, we use the fact that average borrowing interest rates r^b equal the sum of refinancing cost r^s, risk premia ξ, and transaction costs τ (up to the first order). The transaction cost of lending is thus $\tau = r^b - r^s - \xi$. We use charge-offs to measure the risk premium. As reported in Exler and Tertilt (2020), the average charge-offs between 2013 and 2017 are $\xi = 3.3\%$.[25] The average real borrowing interest rate during 2013-2017 is $r^b = 10.6\%$. Exler and Tertilt (2020) construct this data from nominal interest rates on personal loans and credit cards net of the one-year ahead CPI inflation.[26] Thus, the transaction cost of lending is given by $\tau = 10.6\% - 1\% - 3.3\% = 6.3\%$. The rate at which delinquent debt is rolled over (r^r) is fixed at 20% per year, following Livshits, MacGee, and Tertilt (2007).

3.3 Internally Calibrated Parameters

The remaining four parameters—the discount factor, β, the recovery rate of loans that enter bankruptcy, γ, the utility cost of bankruptcy, χ, and the interest rate ceiling, $\bar{r}$—are chosen to target four data moments. These moments are calculated

[24] This is the high end of rates implied by the Laubach and Williams (2003) model for this time.

[25] The authors use the Fed Board of Governors series "chgallsa." Charge-offs measure the value of loans that lenders write off net of potential recoveries as a fraction of total loans. We use charge-offs to pin down the risk premium in borrowing interest rates.

[26] Taken from the Fed Board of Governors series "G.19."

based on data described in Exler and Tertilt (2020) and summarized in Table 2.[27]

First, we target the fraction of consumers declaring Chapter 7 bankruptcy per year. For each year, this fraction is calculated by dividing the total Chapter 7 filings, as reported by the American Bankruptcy Institute, by the total number of households as reported in the Census Bureau's Current Population Survey. The annual average between 2013 and 2017 is 0.45%.

Our second target is the ratio of (gross) unsecured debt to total earnings. This measure uses total revolving credit obtained from the Federal Reserve Board of Governors G.19 series and divides it by personal disposable income from the National Income and Product Accounts. The average between 2013 and 2017 is 6.7%.

As explained above, our target for the average borrowing interest rate is 10.6%. Finally, we include a measure of the dispersion in interest rates. Exler and Tertilt (2020, Table 4) calculate the coefficient of variation from interest rates on loans that carry a positive balance, which in the 2016 SCF was 0.53.

We choose β, γ, χ, and $\overline{r}$ to minimize the sum of the squared relative residuals between the model and the data moments. While the model moments depend jointly on the parameters in a non-linear fashion, we pair the parameters and targets according to the most direct interaction in Table 2. The discount factor plays an important role for the amount of debt in the economy, the utility cost of bankruptcy influences the frequency of default, the bankruptcy recovery rates change the risk premium and, thereby, the average borrowing interest rates, and the interest rate ceiling limits the coefficient of variation of borrowing interest rates. The model matches the data well along all dimensions. We find an annual discount factor $\beta = 0.965$, a utility cost of bankruptcy $\chi = 0.040$, lenders recover $\gamma = 39.5\%$ of bankrupts' income, and the interest rate ceiling is chosen to be $\overline{r} = 106\%$.[28]

[27]The calibration differs from Livshits, MacGee, and Tertilt (2007, 2010) due to the large change in calibration targets as a result of a different time period being targeted (see also Raveendranathan and Stefanidis (2020)). One result of the changed calibration is that borrowers now prefer a laxer bankruptcy regime (lower γ), which was not the case in Livshits, MacGee, and Tertilt (2007, 2010).

[28]The resulting interest ceiling is larger than implied by current usury laws. However, official legal ceilings can be avoided. This ceiling is nonbinding for almost all households in our experiments. As noted in Livshits, MacGee, and Tertilt (2010), having no ceiling can sometimes lead to a (very) small number of people borrowing large amounts at very high interest rates (with little intention of repaying them), which leads to artificially high average interest rates and variance.

Table 2: Internally Calibrated Parameters

Parameter		**Value**	**Target**	**Data**	**Model**
Discount factor	β	0.965	Debt-to-earnings	6.7%	6.67%
Utility cost of bankruptcy	χ	0.040	Bankruptcy filings	0.45%	0.452%
Recovery in bankruptcy	γ	0.395	Avg Borrowing r	10.6%	10.55%
Interest rate ceiling	$\overline{r}$	106%	CV of Borrowing r	0.53	0.532

Notes: Based on data series described in Exler and Tertilt (2020). CV is Coefficient of Variation

4 Behavioral Mistakes and Cross-Subsidization

Our calibrated economy illustrates several interesting insights that arise in an environment with both behavioral and rational agents. While it is not surprising that behavioral borrowers *overborrow*, what is less intuitive is that they also *file too late* for bankruptcy. These mistakes reflect both incorrect beliefs and the *cross-subsidization* of behavioral borrowers by rational borrowers. This cross-subsidization results from the pooling of types, which generally sees behavioral (rational) borrowers paying lower (higher) rates than would be actuarially fair in an economy with full information about each borrower's type. These forces will play a key role in our examination of consumer protection policies in Section 5.

Key to the tractability of our theory of type scoring is that behavioral and rational agents believe they face the same income risk. Although lenders have correct beliefs about the fraction of behavioral agents in the economy, they cannot design separating contracts since both types of agents make identical decisions. Instead, lenders update their beliefs via type scoring, leading to changes in the extent to which behavioral and rational borrowers are pooled over their lifetimes.

4.1 Benchmark Outcomes

Our baseline calibration implies significant differences in borrowing and filings between rationals and behaviorals (see Table 3). Behavioral agents borrow more than rationals, default more frequently, and on average pay higher interest rates. The presence of behaviorals matters for aggregates: It drives up the overall debt-to-earnings ratio, the filings, and the interest rate. Moreover, behavioral agents' incorrect expectations result in their making systematic financial mistakes.

Table 3: Equilibrium Outcomes Across Types

	Realists	Behavioral	Aggregate
Debt-to-earnings	6.4%	8.2%	6.7%
Filings	0.44%	0.53%	0.45%
Interest Rates	10.4%	11.1%	10.5%
Fraction borrowing	20%	23%	20%
Filing too late		0.29%	
Overborrowing (as share of debt)		14.78%	

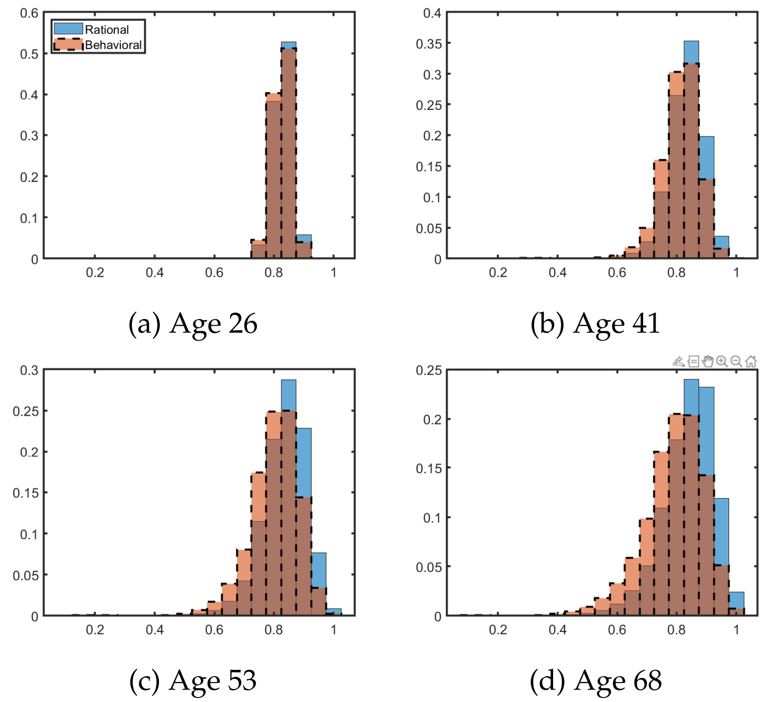
Notes: *"Filing too late"* denotes the percentage of behavioral agents who repay (potentially with new loans) their loans but would immediately file for bankruptcy if informed of their true type. *"Overborrowing"* is reported as a percentage of the behavioral agents' total outstanding debt.

The differential pricing (on average) arises despite the inability of lenders to directly observe a borrower's type. Instead, they update their beliefs on a household type using type scores, which summarize the probability that a household is a realist. This implies that there is some pooling of types for each (interior) type score. Conditional on these scores, lenders quote their credit prices.

A lender's (informed) prior that a newborn household is rational equals their share of the population (in our economy, 0.83). Lenders update these type scores each period based on a household's realized transitory income.[29] Thus, adverse income realizations can result in declining scores for both realists and behaviorals. Conversely, type scores (weakly) monotonically increase for individuals who do not experience an adverse income shock. Since behavioral agents experience negative income shocks more often than realists, their scores are more likely to decline with age. Even so, a lucky behavioral agent's score can remain high for their entire lifetime, while an unlucky rational can see their score fall dramatically as they age.

Figure 1 depicts the evolution of the distribution of type scores by age. At age 26, the type-score distribution is clustered near the initial score of 0.83 as most households have not yet experienced adverse shocks. However, since households that are hit by an adverse (favorable) transitory income shock are more likely to be behavioral (rational), there is some mass below (above) a type score of 0.83.

[29]In our numerical simulations we use a discrete grid with 21 type-score categories. When an updated type-score falls between two grid points, we randomly assign the score to one of these points, with probability weights reflecting the updated score.



(a) Age 26 (b) Age 41

(c) Age 53 (d) Age 68

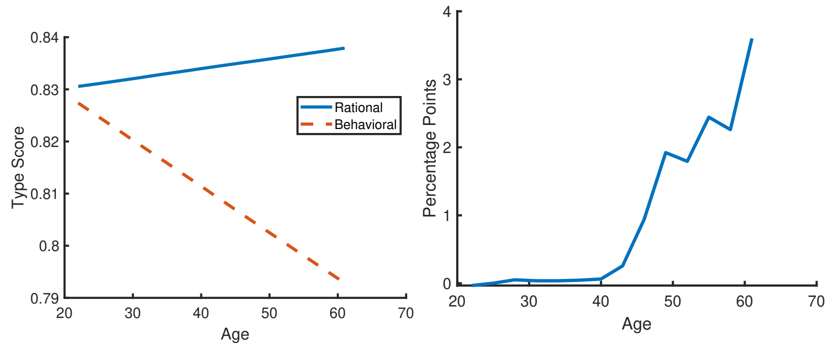
Figure 1: Distribution of Type Scores by Age (PDF)

As households age, the distribution of type scores becomes more dispersed in response to various sequences of realized shocks. This is reflected in the "flattening of the density" with increasing age.

The flattening of the distribution by age results in less pooling of type scores. Early in life, the type-score distribution of over-optimists nearly coincides with that of realists (see Figure 1a). This is no longer true for older households. For older cohorts, the distribution of over-optimists clearly shifts to the left of the distribution of realists (c.f. Figures 1b – 1d). However, even for older consumers there remains substantial pooling of types, especially for intermediate type scores.

Diverging type scores over the life cycle (see Figure 2a) reduce the pooling of borrowers. Consequently, average borrowing interest rates for behavioral borrowers drift away from those of rational borrowers with age (see Figure 2b). In addition to more-accurate type scores and lower cross-subsidization, the rising gap in average interest rates reflects the different debt levels of borrowers. On average, behavioral borrowers carry higher debt levels as they receive negative transitory income shocks more regularly and try to smooth consumption by borrowing.

The pooling of types leads to *cross-subsidization*. Conditional on the level of



(a) Average Type Scores

(b) Average Interest Rate Differential

Figure 2: Pooling Over the Life Cycle

borrowing, cross-subsidization generally sees behavioral (rational) borrowers paying *lower* (higher) than actuarially fair rates. This pattern is apparent in Figure 3, which plots the distribution of the difference between actuarially fair interest payments with perfect information about the types and the actual equilibrium interest payments, $(q(\cdot) - q(\cdot)_{fair})d$. As the figure shows, essentially all behavioral borrowers benefit from cross-subsidization to varying extents, while rational borrowers pay more due to the presence of behavioral consumers.

In Table 3 we report two types of financial mistakes by behavioral agents: filing for bankruptcy too late and overborrowing. Financial mistakes are measured relative to what a household with correct beliefs would choose, holding constant both the equilibrium interest rate schedules (i.e., lenders remain unaware of the agents' types) and agents' past choices (before being informed of their true income risk).

While overborrowing by over-optimists is not surprising, filing too late is less intuitive, especially given that they file more often than rationals (see Table 3). We define "filing too late" as behaviorals who choose not to file for bankruptcy in a given period but would have filed if informed of their true income process. In our calibrated economy, behavioral filings would rise from 0.53% to 0.82% in the period when behavioral borrowers are informed.[30] Over-optimistic expectations

[30]Our measure of "filing too late" (and of over-borrowing) is computed as a one-time "partial equilibrium" exercise based on the ergodic distribution of debts/asset holdings with interest rates fixed at their equilibrium levels. We compute the difference between the decisions taken by behavioral borrowers in equilibrium and those they would have made (at the same asset position) if informed of their true income process. This computation is made at the instance when the information is revealed. General equilibrium effects are discussed in Section 4.2.

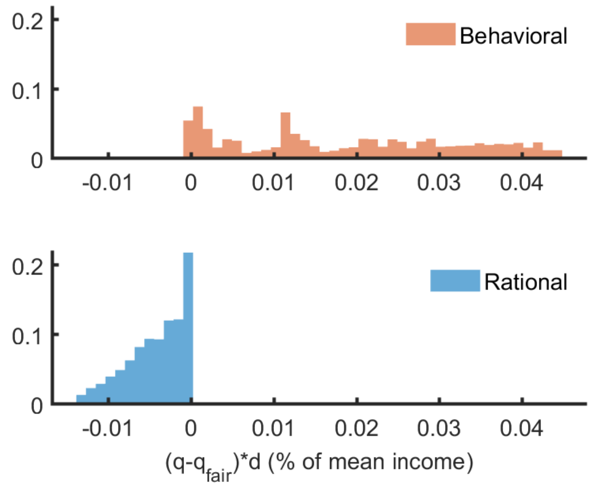


Figure 3: Distribution of Cross-Subsidization (PDF)

of future income thus generate both a greater desire to borrow and a willingness to roll over loans rather than to default right away. Both mistakes arise due to an inaccurately high belief about a behavioral borrower's future ability to repay.

We measure overborrowing as the relative difference between the equilibrium debt held by behavioral agents and the amount they would choose to hold if they were (suddenly) made aware of their true income process. The difference in borrowing between behavioral and rational types reported in Table 3 (8.2% versus 6.4%) actually understates the extent of overborrowing, as behavioral borrowers hold nearly 15% too much debt relative to their rational selves in the same state facing the same prices. Almost half of this overborrowing (6.7pp out of 14.8) arises from not discharging debt through bankruptcy (i.e., "filing too late").

4.2 Decomposition

The borrowing and default decisions of behavioral consumers are shaped by three factors: greater downside income risk (which we refer to as "worse risk"), overoptimistic expectations, and cross-subsidized loan prices through the partial pooling of types. To decompose the contribution of each of these factors, we simulate three counterfactual economies and compare them to the benchmark in Table 4 (the last column repeats the outcomes of behavioral consumers in the benchmark economy). We start from a counterfactual economy that is populated solely by realists,

Table 4: Decomposition Benchmark Transitory Income: Bias vs. Extra Risk

	(1)	(2)	(3)	Benchmark
Income process	Better risk	Worse risk	Worse risk	Worse risk
Beliefs	Realistic	Realistic	Over-opt	Over-opt
Pricing	Individual	Individual	Individual	Cross-subsidized
Debt-to-earnings	6.4%	6.4%	8.2%	8.2%
Filings	0.44%	0.46%	0.51%	0.53%
Interest rates	10.59%	10.38%	9.81%	11.12%
Total borrowers	20%	20%	23%	23%
Filings per borrower	2.25%	2.29%	2.18%	2.27%
Debt-to-earnings of filers	321%	316%	314%	343%
Filing too late			0.27%	0.29%
Overborrowing			14.22%	14.78%

i.e. households who face the better risk income process, hold realistic beliefs, and receive individual loan prices without cross-subsidization, cf. column (1). Next, we consider an economy populated solely by households with correct beliefs but with the worse risk income process, cf. column (2). The third counterfactual isolates the role of over-optimistic beliefs, as this economy is populated entirely by over-optimists, cf. column (3). Finally, column (4) replicates the outcomes for the behavioral consumers in our benchmark economy from Table 3. Compared to column (3), cross-subsidization through partial pooling is added in the last column.

Comparing columns (1) and (2) shows that the direct effects of the greater downside transitory income risk of behavioral borrowers are modest. While greater negative transitory income risk pushes up filings, the quantitative impact is small (0.02 pp, roughly a 4% rise). Moreover, there is little impact on the average debt-to-income ratio as borrowers scale down their debts in line with their income. The fraction of total borrowers, bankruptcy filings per borrower, and the debt-to-earnings ratio of defaulters also remain similar.

However, over-optimistic beliefs have a sizeable effect (compare columns (2) and (3)). Over-optimistic beliefs increase the debt-to-earnings ratio from 6.4% to 8.2%. A key driver of this higher debt level is overborrowing, i.e. due to financial mistakes. Over-optimistic households overborrow by more than 14% in economy

(3).[31] The impact on bankruptcy filings is more modest; filings are roughly 10% higher in the over-optimist economy (0.51% versus 0.46%). This small effect arises largely due to over-optimists filing too late. If suddenly made aware, an additional 0.27% would file for bankruptcy.

The pattern of filing too late induced by over-optimistic beliefs about one's future ability to repay introduces a form of commitment. Filing too late means that behavioral agents roll over their debts for some levels of debt at which their informed selves (cf. column (2)) would choose to default. This results in *lower* average interest rates (compare columns (3) and (2)) due to two effects: First, there are 15% more borrowers when beliefs are over-optimistic (0.23 vs. 0.20) and outstanding debt increases substantially. Second, despite more households borrowing larger sums, filings only increase by about 10%. Consequently, there are *fewer defaults per borrower* and lenders expect to recover *more* of the outstanding loans when borrowers are over-optimistic, which *decreases* average interest rates.

The last column in Table 4 repeats the outcomes of behavioral agents in our benchmark economy. Thus, comparing it to column (3) identifies the effect of cross-subsidized interest rates.[32] Conditional on their type score, behavioral borrowers are pooled with rational borrowers and thus face lower than actuarially fair interest rates. The impact of cross-subsidization on average debt is quite modest as the average debt-to-income ratio and the fraction of borrowers remain nearly constant.

Cross-subsidization has a counter-intuitive impact on the average borrowing rates of over-optimistic households: their average interest rates are *higher* when pooled with rational households (11.12% versus 9.81%). This result arises due to the subtle impacts of cross-subsidization on the probability of default and banks' expected recovery given default. Facing cross-subsidized interest rate schedules changes the distribution of debt holdings, as low debts are cheaper to repay if rolled over. At the same time, large debts can be rolled over and continue to accumulate for longer before a borrower declares bankruptcy. While having little net impact on aggregate debt levels, this results in borrowers filing for bankruptcy with more debt. The debt-to-earnings ratio of defaulters increases by more than

[31] Table 4 compares the debt-to-income ratios across different equilibria, which is different from the reported overborrowing measure. Overborrowing measures the impact of behavioral beliefs on debt-level choices *in a given equilibrium* and, thus, a given history of behavioral debt choices at fixed prices.

[32] Behaviorals in the benchmark constitute 17% of the population vs. 100% in column (3).

9%, from 314% (without pooling, column (3)) to 343% (with pooling, column (4)). Furthermore, there are slightly more overall bankruptcy filings, which leads to 4% more filings per borrower. Cross-subsidized interest rates, thus, result in both a higher probability of default per borrower and lower expected recovery given default. On average, the interest rate for behavioral borrowers *increases* by 131 basis points despite their receiving subsidized loan contracts.

4.3 Removing Behavioral Bias: Full Information Economy

To assess the importance of information frictions on aggregates and consumer welfare we build on the analysis in Section 4.2 and compare the benchmark economy to a full information economy. In the full information environment, behavioral consumers are aware of their true income process and no longer make mistakes.[33] Lenders can identify the type of a borrower and hence condition their pricing of credit risk on whether a borrower is rational or behavioral. As a result, there are no spillovers across types.

Compared to our benchmark, moving to the full information economy has a modest impact on average (economy-wide) debt, filings, and interest rates. The modest impact on aggregates reflects the population composition in our benchmark, as behavioral consumers account for less than a fifth of the population. As a result, although full information has a large effect on borrowing and default by behavioral borrowers, this translates into a much smaller effect on the economy wide aggregates. In addition, with full information, rational borrowers no longer cross-subsidize behavioral ones, as lenders can identify the two types. As a result, rational consumers borrow slightly more, which partially offsets the decline in borrowing by behavioral consumers.

Welfare is higher for both types of agents in the full information economy compared to our benchmark.[34] This finding should not be surprising for the rational consumers. Although identifying behavioral agents does not change a realist's perception of herself, under full information lenders can identify rational borrow-

[33]For ease of comparison with our benchmark economy, we continue to refer to these informed poorer agents as "behavioral." The aggregate economy we examine is the population weighted average of Column (1) and (2) in Table 4.

[34]We adopt a paternalistic welfare measure (see Section 2.4). Perceived welfare is not a suitable measure since, due to over-optimism, the full information economy sees a reduction in the perceived welfare of behavioral agents due to their being fully informed of their true income process.

Table 5: The Full Information Economy

		Benchmark	Full Information
Debt-to-income	Rational	6.37%	6.38%
	Behavioral	8.22%	6.39%
	Average	6.67%	6.38%
Bankruptcy filings	Rational	0.44%	0.44%
	Behavioral	0.53%	0.46%
	Average	0.45%	0.44%
Average interest rates	Rational	10.40%	10.59%
	Behavioral	11.12%	10.38%
	Average	10.55%	10.55%
Paternalistic Welfare	Rational		0.003%
	Behavioral		0.018%
	Average		0.005%

Note: Welfare expressed as consumption equivalence variation (CEV) relative to benchmark.

ers. This means rational borrowers no longer cross-subsidize behavioral borrowers and lowers the interest rate *schedules* rationals are quoted. Rational agents react by borrowing slightly more, which leads to slightly higher *average realized* interest rates in equilibrium. Overall, the full information economy leaves realists with a small increase in welfare of 0.003% consumption equivalence units.

Behavioral agents see a larger welfare gain. This might seem surprising since behaviorals lose the cross-subsidization that the rationals no longer need to pay, which by itself would lower their welfare. However, when behaviorals know their true income process they no longer make mistakes (see Table 4). The gain from eliminating financial mistakes dominates the loss of the cross-subsidization and leads to an overall welfare gain of 0.018% in consumption equivalence units—a gain that is six times as large as the welfare gain for the rationals.[35]

The comparison of our benchmark to the full information economy shows that

[35]The overall welfare gains are still small. This is not surprising since the bias in beliefs is modest to begin with. If agents also had biased beliefs about expense shocks or persistent income shocks, then the welfare effects from moving to full information could be larger.

the presence of behavioral consumers who cannot be directly identified by lenders lowers welfare for both types of consumers. This suggests there is potential scope for regulatory policy to intervene and improve welfare of both types. We turn to this question in Section 5.

4.4 Varying Over-optimism

Our calibration strategy yields an estimate of the fraction of behavioral consumers and their degree of over-optimism. Yet, given the limited data and lack of consensus in the literature we view it as a suggestive rather than a definitive estimate. In this section we investigate the effect of changing the fraction of behavioral consumers, λ, and the degree of over-optimism, ψ. When comparing economies with different λ or ψ, we hold fixed all other parameters.[36] We come back to this analysis when assessing the robustness of our policy experiments in Section 5.

Table 6 reports aggregate and type-specific outcomes as the share of behaviorals in the economy is varied from zero to 100%. As the fraction of behavioral borrowers rises, both average debt-to-income and default rise while average borrowing interest rates decline. These aggregates are driven by changes in the composition of borrowers and individual behavior. The higher debt-to-income ratios and default rates of behavioral consumers directly account for the rise in average debt-to-income as λ rises. The direct effect of more behavioral consumers is partially offset by a change in behavior, as the amount borrowed by each type declines in λ. This reflects the cross-subsidization channel: more behaviorals means that for each rational borrower cross-subsidization payments rise slightly, which makes borrowing more costly. Similarly, borrowing becomes more costly for behaviorals as the amount of cross-subsidization per each behavioral borrower declines.

Table 7 reports what happens as one varies the extent to which behavioral borrowers are over-optimistic. We vary the degree of over-optimism, ψ, between 1 (where the two types are identical) and 2.5.[37] As behaviorals are convinced they face the same income process as rationals, higher ψ translates into a higher degree

[36] Since we do not re-calibrate, this implies a change in aggregate earnings dynamics as the fraction of risky people increases.

[37] Recall that ψ denotes the ratio of the probability of a low transitory income realization of the two types of agents: $\text{Prob}^B(\eta_1)/\text{Prob}^R(\eta_1)$. This means that the expected income of the behavioral income process declines as ψ increases.

Table 6: Varying the Fraction of Behavioral Agents

	Fraction of behavioral borrowers λ					
	0	0.17	0.3	0.5	0.75	1
Debt-to-income						
Rational	6.38%	6.37%	6.36%	6.35%	6.33%	n/a
Behavioral	n/a	8.22%	8.21%	8.21%	8.21%	8.19%
Average	6.38%	6.67%	6.90%	7.27%	7.73%	8.19%
Bankruptcy filings						
Rational	0.44%	0.44%	0.43%	0.43%	0.43%	n/a
Behavioral	n/a	0.53%	0.52%	0.52%	0.51%	0.51%
Average	0.44%	0.45%	0.46%	0.47%	0.49%	0.51%
Average interest rates						
Rational	10.59%	10.40%	10.17%	9.92%	9.61%	n/a
Behavioral	n/a	11.12%	10.86%	10.52%	10.06%	9.81%
Average	10.59%	10.55%	10.41%	10.25%	9.96%	9.81%

of over-optimism. This drives the rise in debt-to-income of behavioral agents, as over-borrowing rises. Although defaults by over-optimists also rise, they rise by (proportionately) less than does debt-to-income due to an increase in filing too late. The combination of a larger rise in debt than filings pushes down average equilibrium borrowing rates (which does not contradict higher interest rate *schedules*, see the discussion in Section 4.2).

These effects show up in the aggregates, albeit more muted. As the degree of over-optimism increases from one to 2.5, borrowing by behaviorals more than doubles, while the economy-wide debt-to-income ratio rises by less than 20%. This is largely due to behaviorals comprising only 17% of the population. Further, borrowing by rationals declines slightly as they face higher interest rate *schedules*. Similarly, filings for behavioral consumers increase by more than 60%, yet average filings increase by only 7%. This more muted aggregate change largely reflects the small fraction of the population who are behavioral, and, to a lesser extent, the fact that filings for rationals slightly decline.

Table 7: Varying the Degree of Over-Optimism

	Degree of Over-Optimism ψ				
	1.00	1.10	1.36	2.00	2.50
Debt-to-income					
Rational	6.37%	6.37%	6.37%	6.31%	6.28%
Behavioral	6.37%	6.87%	8.22%	11.70%	14.43%
Average	6.37%	6.46%	6.67%	7.16%	7.54%
Bankruptcy filings					
Rational	0.44%	0.44%	0.44%	0.42%	0.42%
Behavioral	0.44%	0.47%	0.53%	0.64%	0.71%
Average	0.44%	0.45%	0.45%	0.46%	0.47%
Average interest rates					
Rational	10.79%	10.68%	10.40%	9.73%	9.84%
Behavioral	10.76%	10.89%	11.12%	10.10%	9.19%
Average	10.78%	10.72%	10.55%	9.83%	9.65%

Note: The benchmark economy has $\psi = 1.36$.

4.5 Discussion

Our benchmark results offer several novel insights to the literature. Our work illustrates that cases where lenders are more informed than borrowers need not lead to predatory lending. We adopt the Bond, Musto, and Yilmaz (2009) definition that a "predatory loan" is *one that a borrower would decline if they had the same information as the lender.* Over-optimists are more likely than realists to consider themselves unlucky. While they agree with the estimation of their type score, they do not believe it conveys additional information. However, if made aware, behavioral agents would recognize that their borrowing is subsidized by rationals with the same type score. Hence, they would be happy to continue to borrow at this rate.

Although overborrowing is consistent with the intuition of many, it runs counter to the argument of Hynes (2004) that behavioral consumers could under-borrow since they place too high a probability on repaying debt. We find that behavioral agents overestimate their ability to repay in the future and file for bankruptcy *less often* than if they had an accurate perception of the risks they face. This reinforces the importance of studying financial mistakes such as overborrowing in an environment that is calibrated to match the observed levels of filings and debt.

The benchmark calibration allows us to quantify the credit market spillovers across types (cf. Section 2.5). We find them to be quantitatively modest—the welfare loss for rational borrowers from an economy where 17% of the population is behavioral, relative to an economy without behavioral consumers, is 0.003%. This loss combines both the effect of cross-subsidization and the indirect effects from the changes in interest rates that follow a downgrade in the type score after a negative income shock. The modest quantitative impact of the spillovers may be due to the over-optimism applying only to the transitory income shocks. The insights in Athreya, Tam, and Young (2009) suggest that extending the analysis to include over-optimism over the persistent income process could result in larger spillovers.

5 Consumer Protection Policies

Proponents of credit market regulation often argue it can improve the outcomes of consumers who do not behave rationally or have limited financial literacy.[38] The gap in welfare for both types between our benchmark and the full information economy suggests there is potential scope for regulatory policy to intervene and improve welfare. This leads us to investigate several policies that could alleviate the mistakes of behavioral borrowers, who borrow too much and file too late. Our first experiments compare the effectiveness of small- versus large-scale financial literacy interventions. We next analyze three policies aimed at limiting borrowing—a tax on borrowing, lower default costs and borrowing limits—as well as a policy that makes filing for bankruptcy easier. Since, conditional on type score, over-optimists are indistinguishable from realists, these policies apply to everyone.[39] The results of these experiments are summarized in Table 8. In Appendix B we show that our policy assessments remain similar as one varies the fraction of behavioral consumers or the degree of over-optimism.

[38] Bar-Gill and Warren (2008) argue for regulation because "sellers of credit products have learned to exploit the lack of information and cognitive limitations of consumers," while Campbell (2016) reasons regulation helps, as "when households lack the intellectual capacity to manage their financial decisions, they make mistakes that lower their own welfare and can also have broader consequences for the economy."

[39] Type-score dependent policies are considered in Section 6.

5.1 Financial Literacy Education: A Challenge of Scaling

A natural policy to combat financial mistakes is financial literacy education. By educating over-optimists of their true income risk, education should reduce financial mistakes. Moreover, by directly targeting behavioral consumers a financial literacy program would not directly impact the borrowing options for rational consumers. To formalize this intuition, we evaluate the best case for financial literacy education. We assume it is perfectly targeted at behavioral consumers and makes them fully internalize their true income risks. This hypothetical education campaign can be seen as the upper bound of what financial literacy education can achieve.[40]

First consider a financial literacy intervention that anonymously targets a single behavioral borrower. Since this intervention targets a single borrower, we assume that lenders are unaware of this intervention. This means that we hold fixed the lenders' beliefs about all borrowers, and thus the terms at which our educated borrower can access credit remains the same. Our welfare measure yields the welfare effects for a newborn over-optimist for whom financial literacy education corrects their beliefs during their whole life.

This intervention generates a welfare gain of 0.063% for a newborn over-optimist. These gains reflect a change in borrower decisions, as financial literacy leads to a borrower no longer overborrowing or filing too late. At the same time, the behavioral borrower retains cross-subsidization. The benefits of an anonymous financial literacy intervention in our model appear broadly consistent with empirical findings of positive impacts on consumer behavior after financial literacy programs.[41] In general, these studies have employed modest population sizes and are thus similar in spirit to our exercise.

In a further step, we use our model to examine the impact of extending the financial literacy program to inform all newborn over-optimists of their true income risk. This thought experiment corresponds to our full information economy in Section 4.3, where all consumers are aware of their true income risk. While over-optimists no longer make mistakes, lenders price credit separately for both bor-

[40] In practice, the benefits from a financial literacy program would be lower if one mistakenly advised rational agents that they faced the behaviorals' income process. Even a program that focused on educating bankruptcy filers would face this challenge, as most filers are rational borrowers.

[41] See McGregor (2020) and Lusardi and Mitchell (2014) for a discussion of financial literacy and counselling programs. Kaiser and Menkhoff (2017) conduct a meta-analysis of 126 impact evaluation studies and find that financial education impacts financial behavior and financial literacy.

rowers types. This change in lender behavior means that over-optimist borrowing is no longer cross-subsidized by rationals, which reduces over-optimists welfare gains to 0.018%, i.e. the welfare gain is reduced by roughly three-quarters. This elimination of cross-subsidization of over-optimists results in a small welfare gain of 0.003% for rationals, despite their not being directly impacted by the program.

The reduction of welfare gains as one scales up financial literacy education highlights the importance of taking into account how lenders respond to such programs. By adjusting their interest rate schedules, lenders more accurately price in the underlying default risk of over-optimists. In our environment, this updated pricing of credit risk offsets most of the welfare gains achieved through the small-scale financial literacy education. As a result, our equilibrium model of unsecured credit and risk-based pricing suggests that the welfare gains found in small-scale financial literacy experiments cannot easily be scaled to the entire population.

5.2 Higher Borrowing Costs

A central argument for regulating consumer credit is to preempt overborrowing. This motivates policies aimed at reducing the incentive to (over)borrow, ranging from limiting the roll-over of short term loans, restricting the amount of simultaneous loans, introducing cool-off periods, increasing underwriting requirements, and introducing centralized loan databases. One outcome of many of these regulations is higher lending costs. If individuals overborrow, a higher cost of lending may be beneficial if it discourages "mistaken" borrowing. On the other hand, there is a deadweight cost attached to a higher cost of lending. Moreover, a higher borrowing cost affects everyone, including rational people who use credit correctly.

Our borrowing cost experiment increases the transaction cost of lending by one percentage point, from 6.3% in the benchmark to 7.3%, so that the new risk-free lending rate becomes 8.3%. Higher borrowing costs substantially reduce borrowing but only lower bankruptcy filings by a small amount (see column (2) in Table 8). If a policymaker's objective were to reduce debt and bankruptcies, then this policy could be considered a success.[42] The policy also reduces our measures of filing too late by almost two-thirds, and over-borrowing by roughly one-sixth. Al-

[42] In the popular debate, high debt and many defaults are often pointed to as a problem that regulation should address.

Table 8: Policy Experiments

Parameter	(1) Benchmark	(2) Borrow Cost ↑ $\tau = 7.3\%$	(3) Default Cost ↓ $\gamma = 30\%$	(4) Debt-to-income $\leq 100\%$	(5) Debt-to-income $\leq 100\%$ if $s < 0.8$
Debt-to-income					
Rational	6.37%	5.14%	4.91%	4.74%	5.33%
Behavioral	8.22%	6.73%	6.35%	6.22%	6.79%
Average	6.67%	5.40%	5.15%	4.98%	5.57%
Bankruptcy filings					
Rational	0.44%	0.42%	0.70%	0.42%	0.43%
Behavioral	0.53%	0.51%	0.84%	0.50%	0.51%
Average	0.45%	0.44%	0.72%	0.43%	0.44%
Average interest rates					
Rational	10.40%	11.84%	13.09%	9.61%	10.06%
Behavioral	11.12%	12.69%	14.45%	10.10%	10.50%
Average	10.55%	12.01%	13.37%	9.71%	10.15%
Paternalistic Welfare					
Rational		-0.28%	0.21%	-0.31%	-0.21%
Behavioral		-0.29%	0.23%	-0.31%	-0.25%
Average		-0.28%	0.22%	-0.31%	-0.22%
Financial Mistakes					
Filing too late	0.29%	0.11%	0.20%	0.03%	0.08%
Overborrowing	14.78%	11.27%	13.36%	10.11%	11.34%

Note: Welfare expressed as consumption equivalence variation (CEV) relative to the benchmark.

though behavioral consumers make fewer mistakes, a higher cost of borrowing lowers their welfare. Rational consumers are also worse off. Higher borrowing rates (which in equilibrium increase by more than the increase in τ) tighten the endogenous borrowing limits and hinder consumers' ability to borrow to smooth. As a result, even though mistakes by behavioral consumers are reduced, this policy leaves both types of consumers with lower welfare.

5.3 Lower Cost of Default

To target defaulting too late, we consider a policy that makes default easier. The simplest way to implement this in our model is to lower the default cost. Column (3) in Table 8 reports the results of reducing the required repayment, γ, from 39.5% in the benchmark to 30%. This reduction in default costs substantially increases the default rate of both types of consumers. Facing higher default rates, lenders increase their interest rate schedules, which tightens the endogenous borrowing constraints. As a result, average borrowing interest rates jump to 13.37%. Consequently, households cut back their borrowing. The direct and indirect effects of reduced default costs lower our measure of filing too late by roughly one-third. However, overborrowing declines less, approximately by 10%, since borrowing does not decline as fast as it would for informed borrowers.

Unlike a policy that increases the cost of borrowing, lowering the cost of default increases welfare. However, since rational consumers benefit equally, these gains are not driven by fewer mistakes by behavioral borrowers. Instead, in our calibration, overall default costs are simply too high from a welfare maximizing point of view. Thus, these gains reflect the well documented feature that a more lenient bankruptcy system can improve welfare, as it increases the insurance against adverse shocks (see Livshits, MacGee, and Tertilt (2007) and Exler and Tertilt (2020)).

While in this experiment lower default costs decrease mistakes, this finding is sensitive to the details of the specification. As we show in Appendix B, in a world with a larger degree of over-optimism, lowering default costs increases both types of financial mistakes. Even so, such a policy is still welfare improving.

5.4 Debt-to-Income Limits

A direct way of limiting consumer debt levels is to cap a borrower's debt relative to their income (DTI).[43] Besides formal limits in some markets, these policies are also consistent with the spirit of the Truth in Lending Act, which requires lenders to evaluate borrowers' ability to repay by taking their income into account.[44]

To implement DTI limits in the model, we focus on current persistent income ez. We abstract from transitory shocks, as they contain no information about future income realizations when the debt becomes due. Furthermore, lenders may have little information about contemporaneous temporary income shocks in practice. The debt-to-income ratio relates current borrowing to income: $q(\cdot)d'/(ez)$.[45]

We report the effects of a relatively loose debt-to-income limit of 100% in column (4) of Table 8. Despite being relatively lax, it prohibits large loans, which results in the debt of rational and behavioral agents declining by about 1.6 to 2 percentage points. Smaller outstanding debts are easier to repay and lead to fewer bankruptcies in equilibrium. Fewer bankruptcies lead to lower-risk premia and drive down average borrowing interest rates. Average interest rates are reduced from 10.55% in the benchmark to 9.71% under the debt-to-income limit.

Introducing the debt-to-income limit significantly reduces financial mistakes. Late filing is nearly eliminated (0.03%) and overborrowing drops to 10.11%. Despite these positive effects, the total welfare effects are negative as the cost of constraining consumers' borrowing decisions exceeds the benefit of reducing financial mistakes: Both types of consumers lose 0.31% in consumption equivalence units when debt is capped at current income.

---

[43] We discuss an alternative limit on debt service relative to income in Appendix D.

[44] Regulation Z (§1026.51 Ability to Pay) in the Truth in Lending Act states "*Reasonable policies and procedures include treating any income and assets to which the consumer has a reasonable expectation of access as the consumer's income or assets, or limiting consideration of the consumer's income or assets to the consumer's independent income and assets. Reasonable policies and procedures also include consideration of at least one of the following: The ratio of debt obligations to income; the ratio of debt obligations to assets; or the income the consumer will have after paying debt obligations.*" The Act applies to all forms of consumer credit. DTI limits are also mentioned in the context of macroprudential regulation.

[45] Further details on the definition can be found in Appendix C.

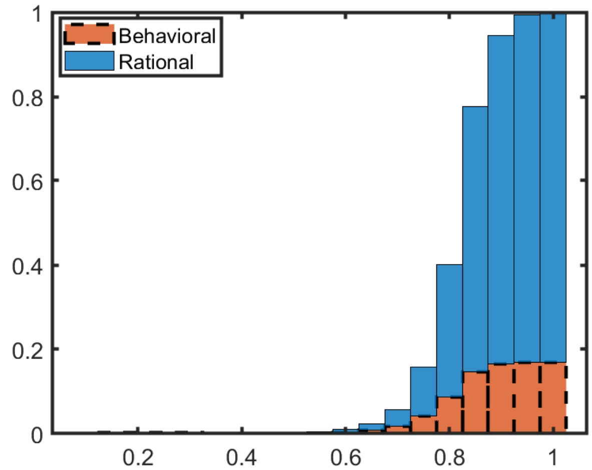


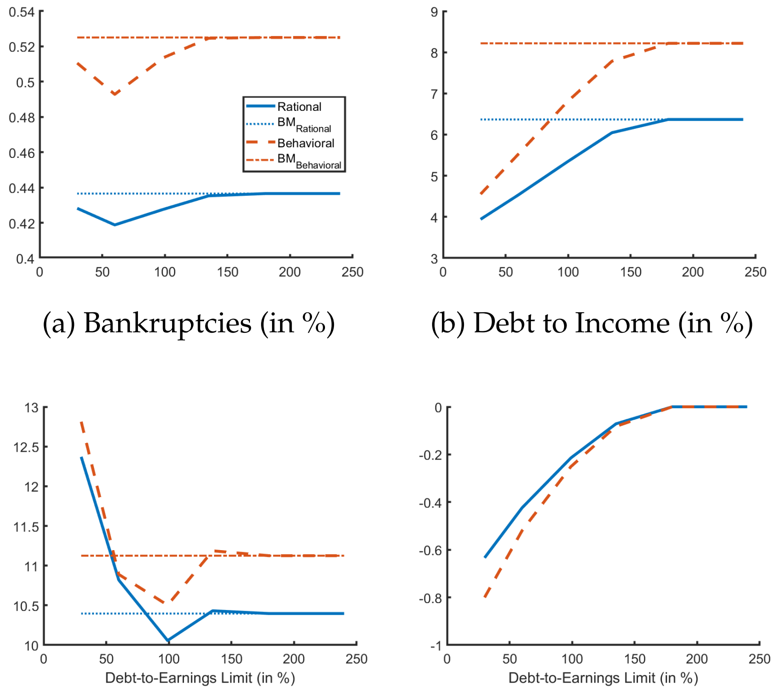
Figure 4: CDF of type scores, split by type. Values based on Table A6 Appendix E.

6 Score-Dependent Consumer Protection Policies

Introducing borrowing limits for all agents can reduce financial mistakes but lowers consumers' welfare. Could a policy that focuses these interventions on consumers that make mistakes be welfare improving? Since policymakers cannot directly observe which consumers are behavioral, we examine the effectiveness of using type scores as a proxy. Intuitively, since borrowers with a low type score are more likely to be behavioral, a policy that applies only to low type scores should reduce financial mistakes with less adverse welfare effects as consumers with high type scores, who are likely rational, would not be restricted by the policy.

We analyze the effect of debt-to-income limits that apply only to consumers below a given type-score threshold along two dimensions: the effect of varying the debt-to-income limit and the effect of varying the type-score threshold below which borrowers are subject to the policy (see Appendix C for further details on the exact definition of the policy in the model).[46] Policies that apply to scores below 0.6 affect almost no one (less than 1%), while most of the population (roughly 95%) have a type score below 0.9 (see Figure 4). However, although 17% of the population are behavioral, their share of the population with low type scores is

[46]Policies targeting households above/below a threshold are common. See Mitman (2016) for an analysis of the 2009 Home Affordable Refinance Program, which effectively subsidized borrowers with loan-to-value ratios between 80 and 125%.



(a) Bankruptcies (in %) (b) Debt to Income (in %)

(c) Interest Rates (in %) (d) Welfare (in % CEV)

Figure 5: Debt-to-Income Limits Below Type Score 0.8

higher as they comprise 26% of those with scores at or below 0.75, and a majority of those with scores at or below 0.4. When targeting behavioral agents, policymakers thus face a trade-off between precision and coverage. On the one hand, lower thresholds affect fewer rational agents inadvertently at the cost of not including some behavioral agents. On the other hand, higher thresholds capture a larger share of behavioral borrowers but also capture more rational agents. Targeted debt-to-income limits—similar to the untargeted limit in Section 5.4 —can reduce debt, defaults, and interest rates. Although successful on these common metrics for credit regulations, targeted policies still lower welfare by restricting access to credit, albeit by less than untargeted limits.

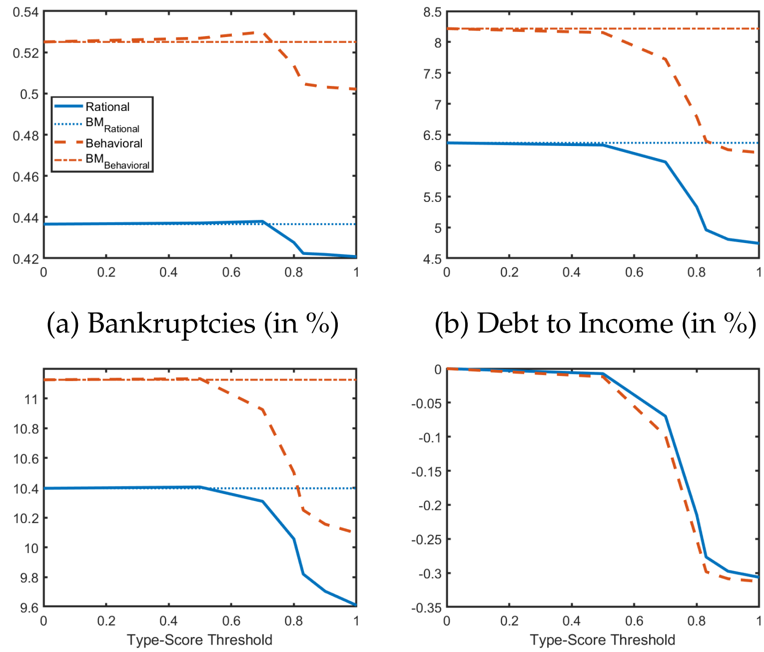
To examine the impact of varying the debt-to-income limit, we fix the type-score threshold to 0.8. In equilibrium, about 16 percent of the population have a type score strictly below 0.8 and are thus subject to the policy. Although behavioral borrowers have lower type scores on average, roughly three-quarters of those affected are rational agents. Table 8 column (5) displays the effects of the 100% DTI limit considered in section 5.4, but now affecting only consumers below a type score of 0.8. Although the overall effects of targeted vs. untargeted policies are similar, a targeted policy has a smaller negative impact on the welfare of rational consumers.

The effects on bankruptcies, debt, interest rates, and welfare are displayed in Figure 5 for debt-to-income limits ranging from 30% to 240% of annual income. Not surprisingly, the lower the debt-to-income limit, the lower the average debt (see panel (b)). Once the limit reaches about 170%, it ceases to bind so that debt returns to its benchmark level. This is a large number, given that the average debt-to-income ratio is only 6.7%.

Do more binding debt-to-income limits also lead to lower filing rates? Initially yes, see panel (a). This is consistent with the effect advocates for regulation have in mind when arguing that preventing people from "borrowing too much" will reduce bankruptcies. However, very tight DTI limits cause filings to increase. Tight limits prevent borrowing by households that are good credit risks but experience temporary bad luck (e.g., an expense shock). Moreover, for large shocks, some households that could have borrowed (and repaid) without declaring bankruptcy are unable to borrow enough with tight DTI limits and declare bankruptcy. Consequently, bankruptcy filing rates and interest rates are u-shaped in the DTI limit. The tighter the limit, the more low-risk consumers stop borrowing so as to preserve their capacity to smooth future adverse shocks by accumulating savings, while the higher-risk, but desperate, continue to borrow. This selection effect sees tight DTIs drive average interest rates above the benchmark level (see Figure 5 panel (c)).

From a welfare perspective, stricter debt-to-income limits are not good policy, even in the range where filings decrease, as average welfare declines (see Figure 5 panel (d)). These welfare effects reflect the costs of limiting access to credit to smooth shocks to income, and the welfare declines are larger for behavioral than for rational households. The larger adverse impact on behavioral borrowers from tight borrowing limits is twofold: since they are more likely to experience negative transitory income shocks, they are more likely to have lower type scores and be borrowing constrained. Additionally, more negative shocks increase the need to borrow for consumption smoothing. Even though this policy lowers debt and, potentially, bankruptcies, it also lowers consumers' welfare.

These negative welfare effects may not hold for alternative type-score thresholds. Thus, we fix the debt-to-income limit at 100%, where interest rates are re-



(a) Bankruptcies (in %)

(b) Debt to Income (in %)

(c) Interest rates (in %)

(d) Welfare (in % CEV)

Figure 6: Debt-to-Income Limit of 100% for Different Type-Score Thresholds

duced the most, and we vary the type-score threshold from 0 to 1 (see Figure 6). The case of a type-score threshold of 0.8 is depicted in Table 8 column (5). Column (4) represents a threshold of 1. For low thresholds, the policy applies to hardly anyone, explaining the lines that are almost flat until about 0.5. Once the debt limit becomes binding for a sizeable fraction of people, average debt starts to fall and bankruptcies also decline. The slight non-monotonicity in bankruptcy rates is related to the selection effect discussed above: There is a range in which more people are affected, reducing their ability to borrow and thus causing them to default. Finally, welfare declines monotonically in the threshold for both types.

Our experiment suggests that while making regulations and restrictions dependent on borrowers' type scores so as to target behavioral borrowers is intuitively attractive, it does not eliminate the adverse effects of limiting debt. Limits on borrowing tend to bind and restrict an individual's borrowing exactly when the need to borrow is highest. Moreover, type-dependent policies face the challenge that adverse transitory income shocks that necessitate borrowing also lower a borrower's type score. If the deteriorated score triggers a DTI limit to bind, this policy will tend to affect unlucky borrowers (regardless of their type) and lower welfare.

7 Conclusion

In this paper, we quantitatively analyze consumer credit markets with behavioral consumers and default. Incorporating over-optimistic borrowers into a standard incomplete-markets economy with unsecured debt and equilibrium default provides several interesting insights. First, by modelling behavioral consumers as over-optimistic and unaware, we develop a tractable theory of type scoring. Second, our work shows spillovers in credit markets to arise in equilibrium between rational and behavioral borrowers. In a world where lenders can only partially infer a borrower's type, partial pooling of rational and behavioral borrowers is likely to ensue. Since the behavioral borrowers in our model are at higher risk of default, in equilibrium they are cross-subsidized by rational borrowers.

We find that over-optimistic beliefs lead behavioral borrowers to make financial mistakes as they overestimate their ability to repay. As a result, they borrow too much and default too late. To address these financial mistakes, we explore several potential credit regulations, including financial literacy education, a tax on borrowing, making default less costly, as well as borrowing limits. Our findings pose a cautionary tale for the effectiveness of consumer financial regulation, as most of the policies we consider either are ineffective in limiting the financial mistakes of behavioral borrowers or are welfare decreasing. Although our policy evaluation is far from the last word on assessing regulatory policies, a lesson from our paper is that regulation likely affects the cross-subsidization implicit in defaults and that this has important welfare consequences that regulators should not ignore.

This paper points to several promising avenues for future research. First, we show that many consumer protection policies can adversely affect borrowers even when targeted at financial mistakes. However, we have naturally not explored all possible policies. Further work should ask whether more nuanced policies could improve welfare. Second, we show transitory shocks to have lasting effects on the terms of credit. This makes consumption smoothing harder when credit is needed most. This mechanism warrants more analysis. Third, our framework in which screening contracts are not feasible naturally leads to pooling. It may be useful in other contexts. Over-optimism also has been documented about health, longevity, and the ability to complete certain tasks. Thus, our basic insights may be useful for understanding health insurance, life insurance, and even employment contracts.

References

Adda, Jerome, and Russell Cooper. 2003. *Dynamic Economics*. Cambridge, Massachusetts: MIT Press.

Agarwal, Sumit, Souphala Chomsisengphet, Chunlin Liu, and Nicholas S. Souleles. 2015. "Do Consumers Choose the Right Credit Contracts?" *Review of Corporate Finance Studies* 4 (2): 239–257.

Arabsheibani, Gholamreza, David de Meza, John Maloney, and Bernard Pearson. 2000. "And a Vision Appeared unto Them of a Great Profit: Evidence of Self-deception among the Self-employed." *Economics Letters* 67 (1): 35–41.

Åstebro, Thomas. 2003. "The Return to Independent Invention: Evidence of Unrealistic Optimism, Risk Seeking or Skewness Loving?" *Economic Journal* 113 (484): 226–239.

Athreya, Kartik, Xuan S. Tam, and Eric R. Young. 2009. "Unsecured Credit Markets Are Not Insurance Markets." *Journal of Monetary Economics* 56 (1): 83–103.

———. 2012. "A Quantitative Theory of Information and Unsecured Credit." *American Economic Journal: Macroeconomics* 4 (3): 153–183.

Balasuriya, J., O. Gough, and K. Vasileva. 2014. "Do Optimists Plan for Retirement? A Behavioural Explanation for Non-participation in Pension Schemes." *Economics Letters* 125 (3): 396–399.

Balleer, Almut, Georg Duernecker, Susanne K. Forstner, and Johannes Goensch. 2021, September. "The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare." CESifo Working Papers No. 9326.

Bar-Gill, Oren, and Elizabeth Warren. 2008. "Making Credit Safer." *University of Pennsylvania Law Review*, pp. 1–101.

Bond, Philip, David Musto, and Bilge Yilmaz. 2009. "Predatory Mortgage Lending." *Journal of Financial Economics* 94 (December): 412–427.

Calvert, Laurent, John Campbell, and Paolo Sodini. 2007. "Down or Out: Assessing the Welfare Costs of Household Investment Mistakes." *Journal of Political Economy* 115 (5): 707–747.

Campbell, John Y. 2016. "Restoring Rational Choice: The Challenge of Consumer Financial Regulation." *American Economic Review* 106 (5): 1–30 (May).

Carroll, Christopher, and Andrew Samwick. 1997. "The Nature of Precautionary Wealth." *Journal of Monetary Economics* 40 (4): 41–71.

Chatterjee, Satyajit, Dean Corbae, Kyle Dempsey, and José-Víctor Ríos-Rull. 2020. "A Quantitative Theory of the Credit Score." *Federal Reserve Bank of Minneapolis, Working Paper*, no. 770.

Chatterjee, Satyajit, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull. 2007. "A Quantitative Theory of Unsecured Consumer Credit with Risk of Default." *Econometrica* 75 (6): 1525–1589.

Chatterjee, Satyajit, Dean Corbae, and José-Víctor Ríos-Rull. 2008. "A Finite-Life Private-Information Theory of Unsecured Debt." *Journal of Economic Theory* 142:149–177.

Corbae, Dean, and Andrew Glover. 2018. "Employer Credit Checks: Poverty Traps versus Matching Efficiency." *NBER Working Paper*, vol. 25005 (September).

Dawson, Chris, and Andrew Henley. 2012. "Something Will Turn Up? Financial Over-optimism and Mortgage Arrears." *Economics Letters* 117 (1): 49–52.

Dodd (CT), Christopher J. 2009, May. "Credit Cardholders' Bill of Rights Act of 2009 - S.5313." *Congressional Record*, Volume 155. U.S. Senate.

Eliaz, Kfir, and Ran Spiegler. 2006. "Contracting with Diversely Naive Agents." *Review of Economic Studies* 73:689–714.

Elul, Ronel, and Piero Gottardi. 2015. "Bankruptcy: Is It Enough to Forgive or Must We Also Forget?" *American Economic Journal: Microeconomics* 7 (4): 294–338.

Exler, Florian, and Michèle Tertilt. 2020. "Consumer Debt and Default: A Macro Perspective." CESifo working paper series 8105, CESifo Group Munich.

Heidhues, Paul, and Botond Koszegi. 2010. "Exploiting Naivete about Self-Control in the Credit Market." *American Economic Review* 100 (5): 2279–2303.

———. 2015. "On the Welfare Costs of Naivete in the US Credit-Card Market." *Review of Industrial Organization* 47:341–354.

Hubbard, R.G., Jonathan Skinner, and Stephen P. Zeldes. 1994. "The Importance of Precautionary Motives in Explaining Individual and Aggregate Saving." *Carnegie-Rochester Conference Series on Public Policy* 40:59–125.

Hynes, Richard M. 2004. "Overoptimism and Overborrowing." *Brigham Young University Law Review*, pp. 127–168.

Kaiser, Tim, and Lukas Menkhoff. 2017. "Does Financial Education Impact Financial Literacy and Financial Behavior, and If So, When?" *World Bank Economic Review* 31 (3): 611–630.

Laibson, David, Jeremy Tobacman, and Andrea Repetto. 2000. "A Debt Puzzle." *NBER Working Paper*, vol. 7879 (September).

Lander, David. 2018. "Strategic vs. Nonstrategic Household Behaviour: An Analysis of U.S. Bankruptcy Filings." mimeo.

Laubach, Thomas, and John C. Williams. 2003. "Measuring the Natural Rate of Interest." *Review of Economics and Statistics* 85 (4): 1063–70 (November).

Livshits, Igor. 2020. "Regulating Consumer Credit and Protecting (Behavioral) Borrowers." *Economic Insights* 5 (1): 14–19.

Livshits, Igor, James MacGee, and Michèle Tertilt. 2003. "Consumer Bankruptcy: A Fresh Start." Federal Reserve Bank of Minneapolis Working Paper 617.

———. 2007. "Consumer Bankruptcy: A Fresh Start." *American Economic Review*, March, 402–418.

———. 2010. "Accounting for the Rise in Consumer Bankruptcies." *American Economic Journal: Macroeconomics* 2:165–193.

———. 2016. "The Democratization of Credit and the Rise in Consumer Bankruptcies." *Review of Economic Studies*, no. 3 (October): 1673–1710.

Lusardi, Annamaria, and Olivia Mitchell. 2014. "The Economic Importance of Financial Literacy: Theory and Evidence." *Journal of Economic Literature* 54 (1): 5–44.

McGregor, Sue L. T. 2020. "Tailoring Bankruptcy Insolvency Education to Ensure Solvency Literacy." *Journal of Financial Counseling and Planning* 31 (1): 55–68.

Mecham, Leonidas Ralph. 2004. *Bankruptcy Basics*. Administrative Office of the United States Courts.

Mitman, Kurt. 2016. "Macroeconomic Effects of Bankruptcy and Foreclosure Policies." *American Economic Review* 106 (8): 2219–2255.

Mueller, Andreas, and Johannes Spinnewijn. 2022. "Expectations Data, Labor Market and Job Search." *Handbook of Economic Expectations, forthcoming*.

Mueller, Andreas, Johannes Spinnewijn, and Giorgio Topa. 2021. "Job Seekers' Perceptions and Employment Prospects: Heterogeneity, Duration Dependence and Bias." *American Economic Review* 111 (1): 324–364.

Nakajima, Makoto. 2012. "Rising Indebtedness and Temptation: A Welfare Analysis." *Quantitative Economics* 3 (2): 257–288.

———. 2017. "Assessing Bankruptcy Reform in a Model with Temptation and Equilibrium Default." *Journal of Public Economics* 145:42–64.

Puri, Manju, and David T Robinson. 2007. "Optimism and Economic Choice." *Journal of Financial Economics* 86 (1): 71–99.

Raveendranathan, Gajendran, and Georgios Stefanidis. 2020. "The Unprecedented Fall in U.S. Revolving Credit." McMaster University mimeo.

Sanchez, Juan. 2017. "The Information Technology Revolution and the Unsecured Credit Market." *Economic Inquiry* 56:914–930.

Sandroni, Alvaro, and Francesco Squintani. 2007. "Overconfidence, Insurance, and Paternalism." *American Economic Review* 97 (5): 1994–2004.

Storesletten, Kjetil, Chris Telmer, and Amir Yaron. 2004. "Consumption and Risk Sharing over the Life Cycle." *Journal of Monetary Economics* 51:609–633.

Sullivan, Teresa A., Elizabeth Warren, and Jay Lawrence Westbrook. 2000. *The Fragile Middle Class*. New Haven and London: Yale University Press.

Weinstein, Neil D. 1980. "Unrealistic Optimism about Future Life Events." *Journal of Personality and Social Psychology* 39 (5): 806.

Zywicki, Todd J. 2013. "The Consumer Financial Protection Bureau: Savior or Menace." *George Washington Law Review* 81 (3): 856–928.

Online Appendix

A Calibration

To measure financial literacy and the frequency of low transitory income realizations, we use data from the 2016 SCF. The 2016 wave added a set of questions on the financial literacy of households. We use the number of correct answers to three questions on the topics of risk diversification, interest rate compounding, and inflation (X7558 to X7560) as a measure of financial literacy. Table A1 shows that only 50% of respondents correctly answered all questions, while 32% answered 2 correctly, 13% had only one correct answer and 4% answered all questions incorrectly. The number of questions answered correctly is highly correlated with education and income (see columns 3 and 4 in Table A1).

Table A1: Educational attainment and total income across financial literacy

Correctly answered questions	Fraction of households	Fraction with first college degree or higher	Mean total income (US-$)
0	0.04	0.22	45,679
1	0.13	0.29	51,968
2	0.32	0.37	65,694
3	0.50	0.62	150,126

Note: First college degree or higher refers to those households in which the highest achieved educational degree of the household head is at least a first college degree. Total income is the total received income of the household from all sources in 2015 (before taxes and deductions).

The 2016 SCF also contains a question (X7650) that asks respondents whether their total income in 2015 was unusually high, low, or normal compared to their expectation during a "normal" year. Table A2 shows the fraction of households that experienced low, normal, or high income, separately for people with high and low financial literacy scores. We find that among those that answered at most 1 question correctly, 19% experienced unusually low income, compared to only 14% of households that answered two or three correctly. Thus, we calculate $\psi = \text{Prob}^B(\eta_1)/\text{Prob}^R(\eta_1) = 19/14 = 1.36$.

Given the overall probabilities of the transitory shock $\text{Prob}(\eta) = [0.1, 0.8, 0.1]$,

Table A2: Unusual income across financial literacy

Correctly answered questions	Fraction of households	Fraction with income unusually low	normal	unusually high
0 or 1	0.17	0.19	0.74	0.07
2 or 3	0.83	0.14	0.77	0.09

the two numbers $\psi = 1.36$ and $\lambda = 17\%$ uniquely determine the transitory income probabilities for both types of agents. To see how, note that by definition $\text{Prob}(\eta_1) = (1-\lambda)\text{Prob}^R(\eta_1)+\lambda\text{Prob}^B(\eta_1)$. Given the definition of ψ, this is $\text{Prob}(\eta_1) = (1-\lambda)\text{Prob}^R(\eta_1) + \lambda\psi\text{Prob}^R(\eta_1)$. Hence, $\text{Prob}^R(\eta_1) = \text{Prob}(\eta_1)(1-\lambda+\lambda\psi)^{-1}$ and $\text{Prob}^B(\eta_1) = \text{Prob}(\eta_1)\times\psi/(1-\lambda+\lambda\psi)$. Finally, $\text{Prob}^T(\eta_3) = 1-\text{Prob}^T(\eta_2)-\text{Prob}^T(\eta_1)$ for $T = \{B, R\}$. See Table 1 for the resulting values.

B Robustness of Policy Experiments

The following experiments show that the effects of consumer protection policies discussed in Section 5 are largely robust to changing the fraction and degree of overoptimism as discussed in Section 4.4. Table A3 reports the effects of consumer protection policies in an economy where 50% of the population are behavioral agents ($\lambda = 0.5$). Table A4 reports the same policy experiments in an economy with a higher degree of over-optimism ($\psi = 2$).[47]

Table A3 shows very similar policy effects in an economy with a higher fraction of behavioral consumers. Welfare always changes in the same direction and by similar amounts. This is mainly due to the observations described in Section 4.4: while averages are significantly affected through a composition effect, changing the fraction of behavioral consumers has little impact on the agents' individual behavior. Consequently, introducing different forms of consumer protection policies has identical qualitative and very similar quantitative effects on both types of agents. There is one exception, albeit of technical nature: Contrary to our main policy experiment in Table 8, introducing a DTI limit only for agents with a type score below 0.8 yields the *same* results as introducing the DTI for the whole population (compare columns (4) and (5)). Since there are 50% behavioral consumers, lenders have a type-score prior of 0.5. This prior implies that virtually all borrowers are

[47]Table 8 presents our benchmark results, where $\lambda = 0.17$ and $\psi = 1.36$

Table A3: Policy Experiments with 50% Behavioral Agents

Parameter	(1) BM with $\lambda = 0.5$	(2) Borrow Cost $\tau = 7.3\%$	(3) Default Cost $\gamma = 30\%$	(4) Debt-to-Inc $\leq 100\%$	(5) Debt-to-Inc $\leq 100\%$ if $s < 0.8$
Debt-to-income					
Rational	6.36%	5.13%	4.91%	4.73%	4.73%
Behavioral	8.21%	6.71%	6.34%	6.20%	6.20%
Average	7.27%	5.91%	5.61%	5.45%	5.45%
Bankruptcy filings					
Rational	0.43%	0.42%	0.68%	0.42%	0.42%
Behavioral	0.51%	0.50%	0.81%	0.50%	0.50%
Average	0.47%	0.46%	0.75%	0.46%	0.46%
Average interest rates					
Rational	9.92%	11.16%	11.77%	9.48%	9.48%
Behavioral	10.52%	11.82%	12.65%	9.91%	9.91%
Average	10.25%	11.53%	12.26%	9.72%	9.72%
Paternalistic Welfare					
Rational		-0.28%	0.21%	-0.31%	-0.31%
Behavioral		-0.29%	0.23%	-0.31%	-0.31%
Average		-0.28%	0.22%	-0.31%	-0.31%
Financial Mistakes					
Filing too late	0.29%	0.09%	0.21%	0.03%	0.03%
Overborrowing	14.77%	11.08%	13.53%	10.17%	10.17%

below the threshold of 0.8 compared to the benchmark economy where the prior was 0.83 and hence the threshold applied to fewer people.

In Table A4, the same policies apply to an economy with behaviorals that are more over-optimistic. Relative to our benchmark calibration, the effects of consumer protection policies are qualitatively the same and even quantitatively quite similar. However, there is one exception: when default costs are lowered (cf. column (3)), financial mistakes *increase*, while in our baseline policy experiment in Table 8 lower default costs decrease mistakes. With $\psi = 2$, behavioral borrowers overestimate their future ability to repay by more. They roll over too much debt and default too late relative to their informed selves. This effect is more pro-

Table A4: Policy Experiments with a Higher Degree of Over-Optimism ($\psi = 2$)

Parameter	(1) BM with $\psi = 2.0$	(2) Borrow Cost $\tau = 7.3\%$	(3) Default Cost $\gamma = 30\%$	(4) Debt-to-Inc $\leq 100\%$	(5) Debt-to-Inc $\leq 100\%$ if $s < 0.8$
Debt-to-income					
Rational	6.31%	5.14%	4.87%	4.74%	5.12%
Behavioral	11.70%	9.78%	9.03%	9.05%	9.23%
Average	7.16%	5.88%	5.53%	5.43%	5.77%
Bankruptcy filings					
Rational	0.42%	0.41%	0.67%	0.41%	0.41%
Behavioral	0.64%	0.63%	1.01%	0.62%	0.63%
Average	0.46%	0.45%	0.73%	0.44%	0.45%
Average interest rates					
Rational	9.73%	11.06%	11.54%	9.27%	9.76%
Behavioral	10.10%	11.61%	12.18%	9.78%	9.99%
Average	9.83%	11.21%	11.71%	9.41%	9.82%
Paternalistic Welfare					
Rational		-0.28%	0.22%	-0.31%	-0.25%
Behavioral		-0.31%	0.30%	-0.30%	-0.30%
Average		-0.29%	0.24%	-0.31%	-0.26%
Financial Mistakes					
Filing too late	0.70%	0.49%	0.93%	0.12%	0.15%
Overborrowing	27.90%	27.22%	31.19%	22.88%	23.33%

nounced in a regime where default costs are low. However, committing more financial mistakes does not change the welfare implications of this reform. Both types would happily trade higher equilibrium interest rates for a cheaper option of default and gaining access to better insurance.

C Details of Borrowing Limit Regulation

Here we provide the equations behind the policies considered in Sections 5.4 and 6. *Debt-to-income limits* are implemented by restricting the bond price of too large loans:

$$q^b(d', z, j, s) = \begin{cases} q^{ub}(d', z, j, s) & \text{if } q^{ub}(\cdot)d'/(ez) \leq B(s) \\ 0 & \text{otherwise.} \end{cases} \tag{A1}$$

Here, q^{ub} is the unrestricted borrowing bond price. Putting a limit on DTI means that as soon as a loan $q^{ub}d'$ is too high relative to income (defined as ez), borrowing is no longer possible. The effective bond price q^b is set to zero in such a case. We define the debt-to-income limit by using ez as a proxy for income. The reason is that banks typically define such limits by using the predicted future income rather than the income in the period when the loan is taken out. Since the transitory income shock has no impact on the ability to repay in the next period, we define the debt-to-income limits using the permanent and persistent income components only.

For a general debt-to-income limit, as in Section 5.4, $B(s) = B$ is independent of the type score. For type-score dependent policies discussed in Section 6, $B(s)$ depends on the score. In our policy experiments, we set one limit for all scores below a threshold, $s < \overline{s}$, while consumers above the threshold face no limit. In other words, we set

$$B(s) = \begin{cases} \overline{B} & \text{if } s < \overline{s} \\ \infty & \text{if } s \geq \overline{s}. \end{cases} \tag{A2}$$

The limit, $\overline{B}$, applies to the amount of debt a person aims to incur in that period. Recall that in our notation, d' is the promised repayment including the interest rate (rather than a conventional measure of debt).

We define the *debt service ratio* (DSR) based on interest payments only. Thus, we assume that agents roll over all of their debt; i.e., $d = d'$. The interest payments that agents face are then $d - q(\cdot)d' = (1 - q(\cdot))d$. Relating it to our income measure, a limit on the $DSR(s)$ is implemented as follows:

$$q^b(d', z, j, s) = \begin{cases} q^{ub}(d', z, j, s) & \text{if } (1 - q^{ub}(\cdot))d'/(ez) \leq DSR(s) \\ 0 & \text{otherwise.} \end{cases} \tag{A3}$$

As above, the limit itself depends on the type score.

$$DSR(s) = \begin{cases} \overline{DSR} & \text{if } s < \bar{s} \\ \infty & \text{if } s \geq \bar{s}. \end{cases} \tag{A4}$$

D Debt Service Ratio Limits

This appendix explores the effects of limiting the debt service ratio (DSR) of borrowers. DSR limits are often used in mortgage markets, where they specify a maximum fraction of monthly income that can be allocated to repaying the principal plus interest. For example, to receive a qualified mortgage, a DSR of 43% or less is required by the Consumer Financial Protection Bureau. A qualified mortgage offers certain legal protections for the lender and, thus, typically lower interest rates for the borrower.

We define the DSR based on interest rate payments, assuming that borrowers roll over their loans without repaying any principal. We focus on a purely interest-based DSR for simplicity as the effects of incorporating principal payments is roughly equivalent to a tighter cap on our interest-based DSR. Formally, the DSR is: $(1 - q(\cdot))d'/(ez)$.

D.1 Untargeted DSR Limits

In contrast to a debt-to-income limit, DSR limits bind more strongly for riskier loans. Because riskier loans carry higher interest rates they are most affected by DSR limits. Thus, DSR limits lower interest rates, the interest rate gap between rational and behavioral agents, and bankruptcy filings more effectively than debt-to-income limits. Furthermore, safe large loans are not restricted by DSR limits. Thus, DSR limits have smaller consequences for overall borrowing and welfare.

Column (2) in Table A5 summarizes the effects of a DSR limit of 45%. The average interest rate decreases to 8.56%. Furthermore, the interest rate gap between rational and behavioral borrowers is nearly closed. Rational borrowers pay 8.55%, on average, versus 8.57% for behavioral borrowers. Since the DSR limit mostly restricts risky loans, bankruptcy filings fall for both types of agents. Since our DSR measure does not include principal, large loans are affected less than under a direct debt-to-income limit. Consequently, the average debt-to-income ratio decreases to a much smaller extent.

A DSR limit cuts late filing roughly by half to 0.13% and over-borrowing by almost a quarter to 11.33%. Still, agents suffer from borrowing restrictions and the total welfare effect is negative. Agents lose 0.03% in consumption equivalence units. Interestingly, even though the policy is less effective at reducing overborrowing and filing too late than the DTI limit of 100% considered in Table 8, the welfare loss is an order of magnitude smaller compared to the DTI limit of 100%.

D.2 Targeted DSR Limits

In line with Section 6, we also investigate DSR limits when they apply only to consumers with a type score below a certain threshold. The logic is the same as before: consumers with a low score are more likely to be behavioral and make financial mistakes. They might need to be protected from "borrowing too much" and ending up unable to repay their debts. We find that the negative aggregate welfare effect of type-dependent DSR limits is nearly cut in half whilst maintaining low equilibrium interest rates (see columns (2) and (3) in Table A5.

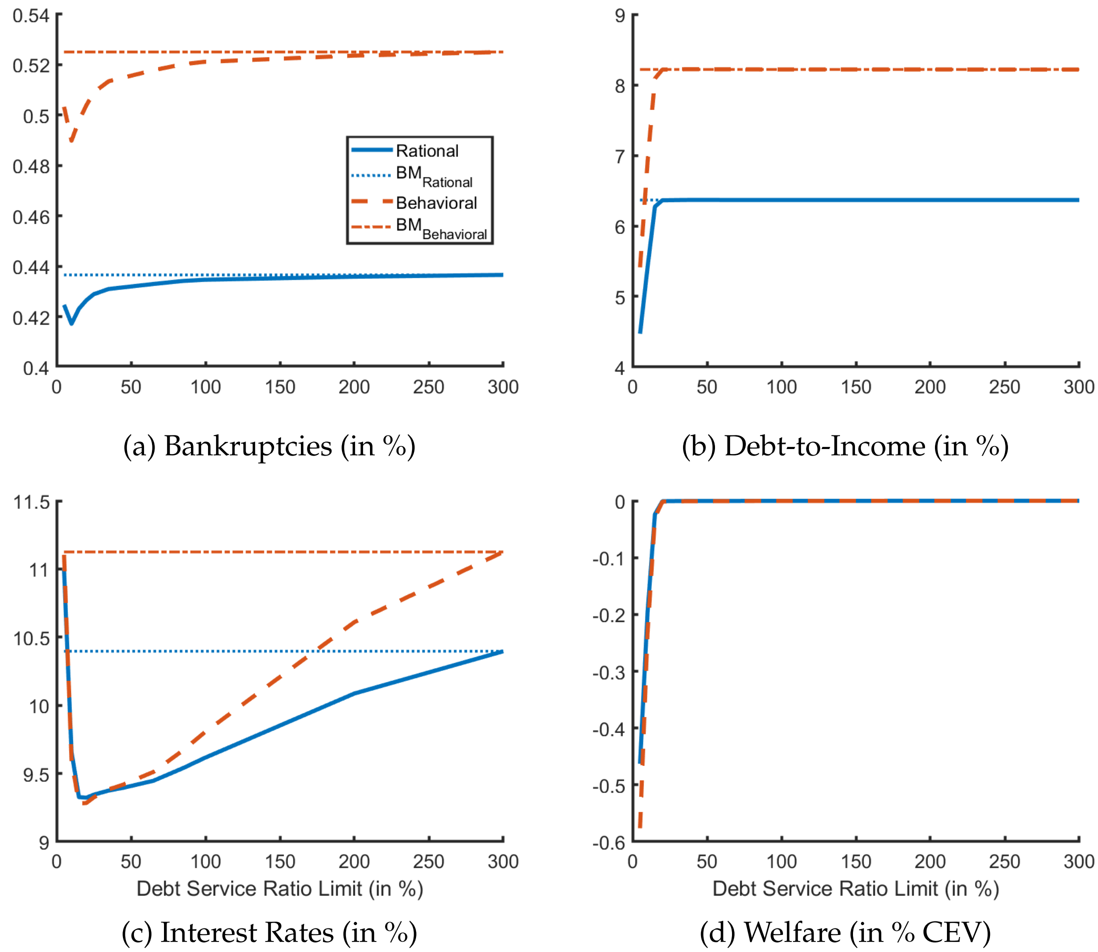
Figure A1 depicts what happens to bankruptcy filings, debt, interest rates, and welfare as the DSR limit moves from from 0 to 300%. The type-score threshold is fixed at 0.8 and about 40% of consumers are affected (see Figure 4). Loose limits (roughly 300% and higher) are nonbinding and hence debt, filings, interest rates and welfare are all at benchmark levels. As DSR limits tighten, filings and debt decline and interest rates fall. However, filings and interest rates are non-monotonic in the limit. For very tight limits, filings begin to rise and interest rates also increase. The reason is similar to that for DTI limits: very tight limits prevent good credit risks from borrowing and can thus push borrowers into bankruptcy.

In contrast to debt-to-income limits, interest rates remain below the benchmark

Table A5: Debt-Service-Ratio Experiments

Parameter	(1) Benchmark	(2) Debt Service Ratio $\leq 45\%$	(3) Debt Service Ratio $\leq 45\%$ if $s < 0.8$
Debt-to-income			
Rational	6.37%	6.23%	6.27%
Behavioral	8.22%	8.05%	8.10%
Average	6.67%	6.53%	6.57%
Bankruptcy filings			
Rational	0.44%	0.41%	0.42%
Behavioral	0.53%	0.49%	0.50%
Average	0.45%	0.43%	0.44%
Average interest rates			
Rational	10.40%	8.55%	9.33%
Behavioral	11.12%	8.57%	9.28%
Average	10.55%	8.56%	9.32%
Paternalistic Welfare			
Rational		-0.03%	-0.02%
Behavioral		-0.03%	-0.03%
Average		-0.03%	-0.02%
Financial Mistakes			
Filing too late	0.29%	0.13%	0.16%
Overborrowing	14.78%	11.33%	11.90%

Note: Welfare is expressed as the consumption equivalence variation relative to the benchmark.



(a) Bankruptcies (in %)

(b) Debt-to-Income (in %)

(c) Interest Rates (in %)

(d) Welfare (in % CEV)

Figure A1: Debt Service Ratio Limits Below Type Score 0.8

even for very tight DSR limits. One reason is that unconstrained safe borrowers can still use debt to smooth adverse shocks. Hence, there is a smaller selection effect that drives up interest rates when DSR limits are tight. Another reason is that DSR limits preclude high interest rate loans, mechanically driving down average interest rates.

To investigate the effects of changing the type-score threshold, we fix the DSR limit to 45% (which is shown to effectively reduce interest rates and bankruptcies) and vary the type-score threshold from 0—no one is subject to the DSR limit—to 1—everyone is subject to the DSR limit. The latter corresponds to column (2) in Table A5. Overall, Figure A2 resembles the case of debt-to-income limits (see Figure 6): the higher the type-score threshold, the more people are affected and hence filings, interest rates, and debt decline. However, the effect on average debt and welfare are much smaller than for debt-to-income limits. For example, setting a type-score threshold of 70, average interest rates for both types of borrowers are 10% and 10.4% (compared to 10.4% and 11.1% without the DSR limit). Defaults decrease slightly, too. However, average debt remains almost constant and the negative welfare effect is below 0.01% in consumption equivalence units. While this policy is still welfare inferior to no regulation, regulating the DSR seems to achieve lower interest rates and lower interest rate spreads between behavioral and rational borrowers at a lower welfare cost compared to regulating the DTI.

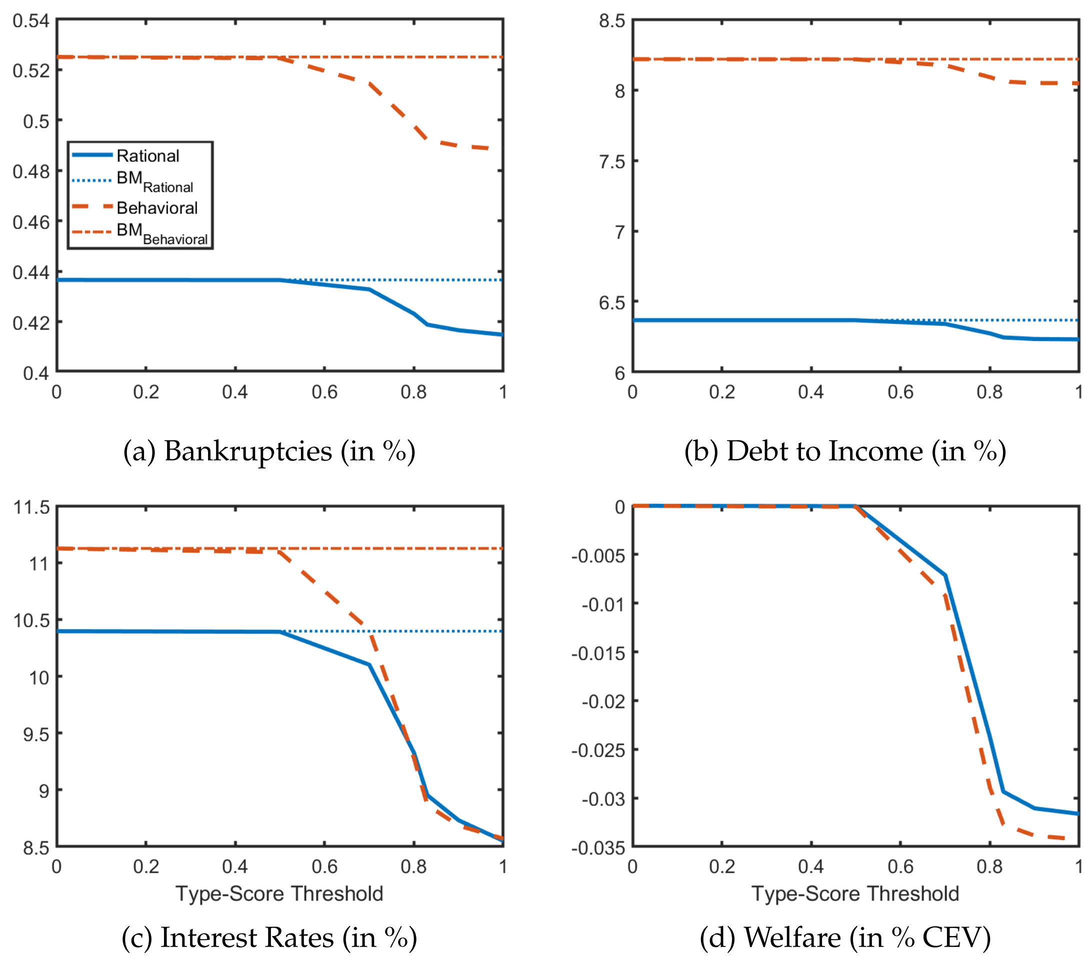


Figure A2: Debt Service Ratio Limit of 45% for Different Type-Score Thresholds

E Ergodic Distribution of Type Scores

Table A6: Type-Score Distribution in Benchmark Calibration

Score	Fraction of Population with Score	% Behavioral within Bin
≤ 0.35	0.00%	–
0.40	0.01%	50.85%
0.45	0.04%	46.61%
0.50	0.10%	43.22%
0.55	0.25%	38.98%
0.60	0.58%	35.34%
0.65	1.45%	31.31%
0.70	3.37%	27.89%
0.75	10.09%	23.43%
0.80	24.21%	18.79%
0.85	37.56%	15.82%
0.90	16.90%	11.54%
0.95	4.83%	8.24%
1.00	0.62%	5.85%