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Consumer Credit with Over-Optimistic Borrowers

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Abstract

There is active debate over whether borrowers' cognitive biases create a need for regulation to limit the misuse of credit. To tackle this question, we incorporate overoptimistic borrowers into an incomplete markets model with consumer bankruptcy. Lenders price loans, forming beliefs—type scores—about borrowers' types. Since over-optimistic borrowers face worse income risk but incorrectly believe they are rational, both types behave identically. This gives rise to a tractable theory of type scoring as lenders cannot screen borrower types. Since rationals default less often, the partial pooling of borrowers generates cross-subsidization whereby over-optimists face lower than actuarially fair interest rates. Over-optimists make financial mistakes: they borrow too much and default too late. We calibrate the model to the US and quantitatively evaluate several policies to address these frictions: reducing the cost of default, increasing borrowing costs, imposing debt limits, and providing financial literacy education. While some policies lower debt and filings, they do not reduce overborrowing. Financial literacy education can eliminate financial mistakes, but it also reduces behavioral borrowers' welfare by ending cross-subsidization. Score-dependent borrowing limits can reduce financial mistakes but lower welfare.

Bank topics: Credit and credit aggregates; Credit risk management; Financial system regulation and policies

JEL codes: E21, E49, G18, K35

1 Introduction

The rise in consumer credit and personal bankruptcies has renewed 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 (some) consumers overborrow due to behavioral biases, or that less sophisticated borrowers are exploited by sophisticated lenders, leaving some "trapped in debt."[1] Opponents of additional financial regulations often point towards the adverse effects on rational borrowers who face higher borrowing costs and reduced access to credit as a result of costs arising from regulations (e.g., Zywicki (2013)). Although this debate is far from settled, the 2008 Financial Crisis helped crystallize support for regulatory reforms, as evidenced by 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 framework with "rational" and "behavioral" households to analyze consumer financial regulation.[3] Given that much of the debate over regulation focuses on credit cards, our framework features unsecured consumer credit and the option for consumers to default and not repay their debts. Specifically, we introduce over-optimistic borrowers into a standard incomplete markets life-cycle economy with unsecured debt and equilibrium default (Chatterjee et al. 2007; Livshits, MacGee, and Tertilt 2007). A central feature of our model is that the identity of behavioral borrowers is not directly observable. As a result, lenders price credit endogenously based on beliefs about a borrower's type, which are updated over a borrower's lifetime.

The co-existence of behavioral and standard 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.[4] We show that over-optimistic consumers make

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

[2] The CFPB, with a mandate to regulate credit products, was part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. The CARD Act restricted credit card fees and increased disclosure requirements.

[3] The extent of consumer non-rationality in consumer finance is debated in the literature. Telyukova and Wright (2008) and Telyukova (2013), for example, argue that the credit card debt puzzle can be largely explained by households' need for liquidity. Bonaparte, Cooper, and Sha (2019) argue that incorporating irrational consumers does not improve their model's ability to match the turnover of stock trades. Our paper is not intended to settle this debate but examines the trade-offs of alternative regulations if over-optimistic consumers exist.

[4] Campbell (2016) also argues for models where both types of agents meaningfully interact.

mistakes both in their borrowing and default decisions. These mistakes suggest possible welfare gains from regulation. We thus analyze several potential policies. We find that even when policies reduce mistakes, they are often not welfare improving.

We model behavioral consumers as being overly optimistic about future income for two reasons. First, this assumption gives rise to a tractable model of type scoring and partial pooling of behavioral and non-behavioral consumers. 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), and that they generally underestimate the probability of experiencing negative events (Weinstein 1980).[5] Motivated by these findings, we assume that behavioral consumers place too high (low) probabilities on positive (negative) transitory income shocks.[6]

Since we assume over-optimists believe they face the same risks as rational consumers, behavioral consumers differ from realists in being more prone to shocks *and* being unaware of the higher 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. Respondents in the Survey of Consumer Finances (SCF) with low financial literacy scores report being surprised by low income realizations more often than individuals with high financial literacy. 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 idiosyncratic earnings 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 over the uncertainty they face and over-optimists who believe they are realists (and—conditional on their state—behave as realists) but actually face systematically higher risk. If households do not default, then they

[5]Using a British household survey, Dawson and Henley (2012) find that 30% of households are over-optimistic about their future income. Balasuriya and Vasileva (2014) find that over-optimists save less for retirement. Other work finds that some consumers are over-optimistic about their survival (Puri and Robinson 2007) and the time it takes to complete everyday tasks (Buehler, Griffin, and Ross 1994).

[6]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 among U.S. consumers.

can borrow or save in a one-period bond that is priced in a competitive debt market.

Financial intermediaries observe household earnings, age, and current debt or asset positions, but they cannot directly observe whether a household is an over-optimist or a realist. Instead, financial intermediaries form beliefs—*type scores*—over 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 and there is no way for lenders to design screening contracts. As consumers age, lenders update their beliefs about a borrower's type based on observed realizations of their idiosyncratic uncertainty. The model thus provides a tractable theory of type scoring.

We find that behavioral consumers have a quantitatively significant impact on equilibrium aggregates when we calibrate to the U.S. economy. Although they comprise only 17% of the population, the debt-to-income ratio is 9% higher, bankruptcy filings are 8% higher, interest rates 4% higher and the number of borrowers 5% higher, compared to an economy with only rational people. Our decomposition shows that this is primarily driven by the incorrect beliefs of behaviorals rather than by their higher income risk. As the fraction of over-optimists in the economy increases, interest rate schedules rise and both types borrow and default less. However, aggregate debt and bankruptcies increase due to a composition effect: a larger population of behavioral agents means the economy has more over-optimistic households that borrow and default more often.

Behavioral consumers make mistakes as they over-borrow and file too late compared to what a fully informed version of themselves would do when faced with the same (equilibrium) prices. In our calibrated economy, if suddenly made aware, behavioral consumers would borrow 3% less and an additional 0.3% would file for bankruptcy. This arises because over-optimistic beliefs about future income encourages borrowers to postpone defaulting as they expect to repay their debt. Ex post, however, over-optimists are systematically surprised by lower income realizations and are 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 that target the mistakes of behavioral consumers.[7] First, we reduce the cost of default, inducing over-optimistic people to default earlier. Second, to target overborrowing, we make borrowing more costly via a proportional transactions tax.[8] Third, we investigate "financial literacy education," where we inform people of their true type, inducing them to internalize the true probabilities into their beliefs.

These policy experiments offer interesting insights into who wins and who loses from credit regulation. Reducing default costs leads to higher 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 behavioral borrowers. Instead, in our calibrated model, overall default costs are simply too high from a welfare maximizing point of view. We also find that a tax on borrowing lowers the welfare of both types of consumers. Somewhat paradoxically, a tax on borrowing also increases the extent of overborrowing. While a tax on borrowing leads to substantially lower debt for behavioral consumers, debt falls by less than it would for a fully aware consumer. Thus, our measure of overborrowing rises. Surprisingly, financial literacy education makes rationals better off at the expense of over-optimists. While this policy eliminates behavioral borrowers' mistakes (which in itself is unambiguously welfare improving), it also ends cross-subsidization. As the loss of cross-subsidization dominates the elimination of mistakes, behavioral consumers are left worse off. Rational people, conversely, benefit from no longer being pooled with the higher-risk over-optimists.

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) limits targeted at borrowers with a low type score (and hence a high probability of being behavioral). We find that such limits lower both borrowing and default, which are typically prime regulatory objectives. However, they also tend to lower welfare by restricting access to credit for some borrowers. This suggests that metrics based on debt and default may provide a misleading guide to the effectiveness of credit market regulations.

[7]To evaluate the welfare of behavioral agents, we use paternalistic welfare weights that use the true probabilities rather than the over-optimistic beliefs.

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

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.[9] Two exceptions are Laibson, Tobacman, and Repetto (2000) and Nakajima (2012, 2017), who each 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 behavioural and rational borrowers. Nakajima (2017) analyzes the implications of alternative bankruptcy rules for behavioral and rational consumers and, like us, finds that behavioral and rational consumers can disagree about the desirability of reforms. However, there are no spillover effects in Nakajima (2017) model, as 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.

Our work is also related to a recent theoretical IO 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. The extra fees paid by behavioral consumers benefit either a lender or, in models with competitive banking, the rational borrowers who benefit from lower prices (interest rates). 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 in equilibrium. This is important both because risk-based pricing is frequently cited as justifying higher pricing for some consumers and high default rates are a major concern in the policy debate. We show that the possibility of default leads to a natural form of cross-subsidization that benefits behavioral consumers, which is absent in models without default.

Although our model features lenders who are better informed than borrowers about

[9] Agarwal et al. (2015) use a large administrative data set from a large bank and find that 40% of consumers do not choose the cheapest credit card contract. Lander (2018) argues that non-strategic borrowers can help match characteristics of bankruptcy filers. Calvert, Campbell, and Sodini (2007) find that less financially sophisticated Swedish households tend to underinvest in higher return (but riskier) assets.

default risk, our equilibrium does not feature predatory lending. 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. Conditional on each household's type score, lenders in our model pool borrowers with correct beliefs about future default risk with borrowers who incorrectly share the same beliefs. Contrary to Bond, Musto, and Yilmaz (2009), however, over-optimists are aware of their type score as it is a function of past income shocks. Being ignorant of their fundamentally higher risk, they instead believe that past bad luck has led to their being pooled with higher-risk borrowers. As a result, they agree to the loan contract offered to them. Moreover, 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.

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 Rios-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, Chatterjee et al. (2020) add unobservable extreme-value shocks to household's 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. Thus, our approach avoids issues arising from possible screening contracts and the potential non-existence of equilibria due to cream skimming. Unlike other credit-scoring papers', our model incorporate behavioral consumers.

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 on behavioral and rational types. In Section 6, we consider type-score dependent policies. Finally, 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 $\lambda \in (0, 1)$ 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 idiosyncratic risk as realists. 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.[10] Markets are incomplete as the only financial instruments are one-period bonds. Since households can default on their loans, debt is 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 the population that are over-optimists, λ, they cannot directly observe a consumer's type. Thus, lenders form beliefs over 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 .

The consumer income and expense shocks are realized at the beginning of each period. Lenders observe these realizations and update type scores. Consumers then decide whether 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

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

a utility cost of bankruptcy. $T \in \{R, B\}$ denotes a household's type: rational ($T = R$) or behavioral ($T = B$). Behavioral consumers have over-optimistic expectations $\mathbb{E}^B$, which influence their consumption-savings choice as well as their default choice, δ.

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 of a household. 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 choses 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 more details). The budget constraint of a bankruptcy filer 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. They believe they face the same distribution of transitory income shocks η as realists do. Hence, behavioral consumers are over-optimistic about their transitory income risk.

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.[11]

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. Summarizing,

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

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

2.1.2 Bankruptcy

Consumers can file for bankruptcy. Similar to 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).[12] Individuals cannot file for bankruptcy in consecutive three-year periods, which captures the six-year exclusion from a repeat Chapter 7 bankruptcy. Furthermore, filers must repay a fraction γ of their income when they declare bankruptcy.[13] Because filers cannot save or borrow, the budget constraint in bankruptcy states that filers consume their income net of garnishment:

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

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 filing, creditors have no claims on a bankrupt's future income or assets, as is the case after a Chapter 7 filing.

[11] Note that behavioral consumers do not update their beliefs as they age; they interpret bad transitory income realizations simply as bad luck, which can also befall rational agents.

[12] 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.

[13] 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).

2.2 Financial Intermediaries

Financial intermediaries are competitive and can borrow and save at the exogenous risk-free rate, r^s. When making loans to households, they incur a proportional transaction cost, τ. Lenders offer each borrower a personalized bond-price schedule, which is a function of the face value to be repaid next period, d'. Intermediaries take into account expected losses from default when determining the bond-price schedule, $q(d', \cdot)$. This price schedule depends on the borrower's age, j, current realization of the persistent income state, z, the amount, d', being borrowed, and the lenders' perception of the borrower's type, T. The latter is summarized by a *type score*, s.[14]

Type scores represent the probabilities that intermediaries attach to a household being rational. Although intermediaries cannot directly observe a household'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. A household that starts a period with type score s and experiences shock realizations η will have the type score updated to

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

All households enter the economy with the informed prior $s_0 = 1 - \lambda$.

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), 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.

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

2.3 Equilibrium

Perfect competition and free entry result in lenders earning zero expected profits on each loan. Conditional on observable characteristics (persistent labor 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. If a borrower defaults, banks recover a fraction $\gamma y/(d' + \kappa')$ of the loan's face value from the garnisheed income, 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

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

Consumers take the equilibrium bond-price schedule as given. 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.[15] 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, $T \in \{R, B\}$:

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

[15]Delinquency addresses the possibility of an empty budget set for a consumer who is ineligible for bankruptcy but draws a large expense shock. The only debts in this case stem from the expense shock.

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

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

An equilibrium is a set of value functions, optimal decision rules for consumption $c(\cdot)$, debt levels $d'(\cdot)$ and default for consumers, 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 what a planner would attach to their consumption stream (or the value of a behavioral agent if they were made aware of the true income process). Since over-optimists place excessive weight on positive outcomes and insufficient weight on adverse outcomes, their expected utility exceeds the average realized outcomes of behavioral individuals.

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

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

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 over 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 second qualitative insight is that transitory income shocks can have long-lasting effects on access to credit. Realizations of 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 when a household desires 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.[16] We also use the Survey of Consumer Finances (SCF) from 2016, which is the most recent available wave. Our calibration proceeds in two steps. First,

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

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.

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).[17]

We follow Livshits, MacGee, and Tertilt (2007) in parameterizing the expense shocks to U.S. estimates of medical expenses, divorces, and unplanned parenthood.[18] 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 only hit 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 in the model not even the consumers themselves know that they are behavioral and face a different income process. 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.[19]

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

[18]Note that the original expense-shock process was based on data on medical expenses, unwanted births, and divorces from the mid-1990s. However, there was little change in these numbers over the last three decades. Medical out-of-pocket spending remained essentially flat as a fraction of median household income. The number of births per 15-44 women also remained flat. The number of unwanted births slightly increased, at the same time divorces per 1,000 population declined a bit.

[19]The overall income process is consistent with Storesletten, Telmer, and Yaron (2004), Hubbard, Skinner, and Zeldes (1994), and Carroll and Samwick (1997). We map annual values from the literature into triennial and employ the Tauchen method (see, e.g., Adda and Cooper (2003)) to discretize income shocks.

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 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. Each retiree receives a deterministic pension of 20% of the average income in the economy, plus 35% of their final persistent income realization.

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 behavioral agents 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 usual. 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 that they also experience negative income shocks more often. In other words, we assume a negative correlation between being overly optimistic and expected income. Since we equate over-optimism with financial illiteracy, this is an assumption we can check in the data. Indeed, we find that financial literacy is highly correlated with income and education. See Table 7 in Appendix A for further details.

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

3.2 Financial Market

We set the safe interest rate to $r^s = 1\%$ annually.[20] 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 $\xi = 3.3\%$.[21] 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.[22] Thus, the transaction cost of lending is given by $\tau = 10.6\% - 1\% - 3.3\% = 6.3\%$. Finally, 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 go into bankruptcy, γ, the utility cost of bankruptcy, χ, and the interest rate ceiling, $\overline{r}$—are chosen to target four data moments. These moments are calculated based on data described in Exler and Tertilt (2020) and summarized in Table 2 below.

First, we target the fraction of consumers declaring Chapter 7 bankruptcy per year.

[20] This is at the high end of the neutral real rates implied by the Laubach and Williams (2003) model over this time period.

[21] 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.

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

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 Fed Board of Governors G.19 series and divides it by annual personal disposable income from the National Income and Product Accounts. The average between 2013 and 2017 amounts to 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 $\overline{r} = 106\%$.[23]

4 Behavioral Mistakes and Cross-Subsidization

We begin by examining how the presence of behavioral agents affects the pricing of credit as well as the levels of debt and bankruptcy filings when our economy is calibrated to match aggregate filings and unsecured debt. One key observation is that the partial pooling of behavioral and rational borrowers affects the terms at which both types of agents access credit. This in turn influences borrowing and default decisions.

[23] The resulting interest ceiling is larger than implied by current usury laws. However, official legal ceilings can be avoided. See Livshits, MacGee, and Tertilt (2010) for a discussion.

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

Data Sources: see text, based on data series described in Exler and Tertilt (2020).
CV denotes Coefficient of Variation

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 (partial) pooling of types, which generally sees behavioral (rational) borrowers paying lower (higher) rates than would be actuarially fair. 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 over 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). Not surprisingly, behavioral agents borrow more than rationals, default more frequently, and on average pay higher interest rates. The presence of behavioral consumers matters for aggregates: It drives up the overall debt-to-earnings ratio, the filings and the interest rate. Moreover, behavioral agents' incorrect expectations about future income result in their making systematic financial mistakes.

The differential pricing (on average) arises despite the inability of lenders to directly

Table 3: Equilibrium Outcomes Across Types

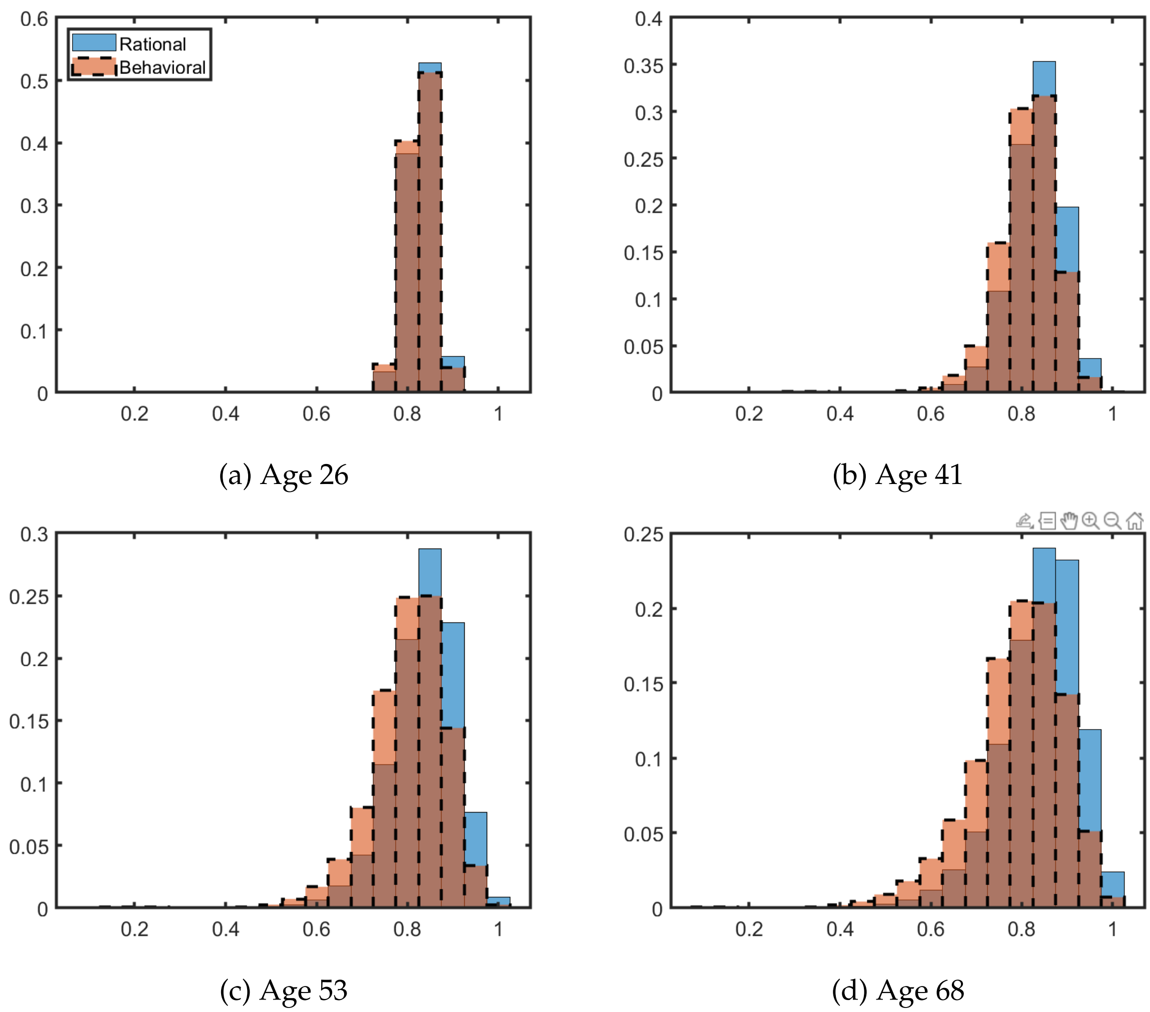
	Realists	Behavioral	Aggregate
Debt-to-earnings	6.4%	8.2%	6.67%
Filings	0.44%	0.53%	0.45%
Interest rates	10.4%	11.1%	10.6%
Fraction borrowing	20%	23%	20%
Overborrowing (as share of debt)	-	2.8%	-
Filing too late	-	0.29%	-

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 new-born 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. Thus, adverse income realizations can result in the scores declining 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 decline 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. 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 Panel 1a). This is no longer true for older households. For older cohorts, the distri-



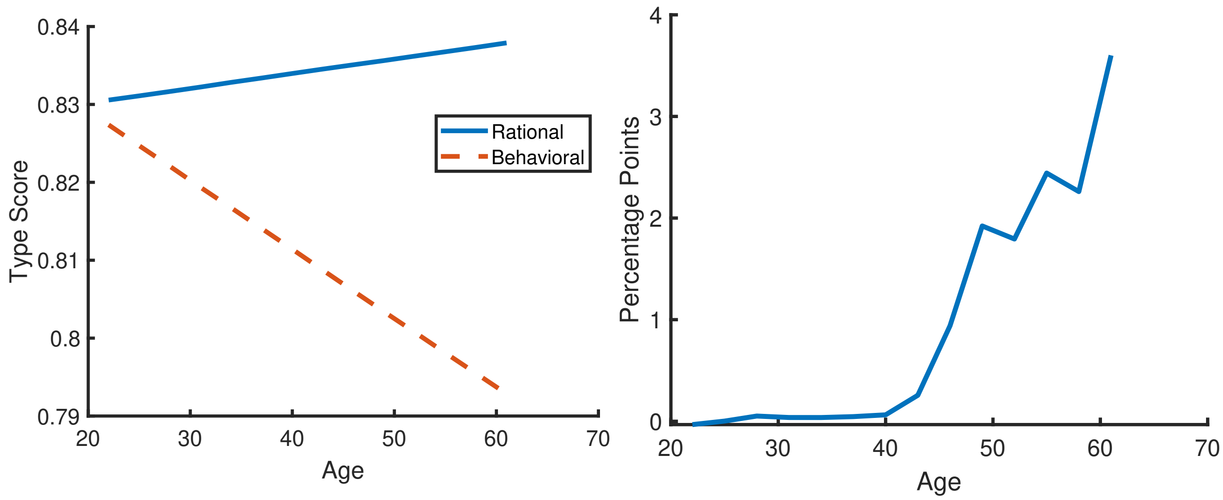
(a) Age 26

(b) Age 41

(c) Age 53

(d) Age 68

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



(a) Average Type Scores

(b) Average Interest Rate Differential

Figure 2: Pooling Over the Life Cycle

bution of over-optimists clearly shifts to the left of the distribution of realists (c.f. Panels 1b – 1d). However, even for older consumers there remains substantial pooling of types, especially for intermediate type scores.

The divergence in type scores over the life cycle (see Figure 2a) reduces 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 the effect of more-accurate type scores, which reduces cross-subsidization, the rising gap in average interest rates reflects the different debt levels of borrowers. On average, over-optimists carry higher debt levels as they receive negative transitory income shocks more regularly and try to smooth consumption by borrowing.

Partial pooling of types leads to *cross-subsidization*. Conditional on the level of 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 (without pooling) and the actual interest payment (i.e., $(q(\cdot) - q(\cdot)_{fair})d$). 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 equi-

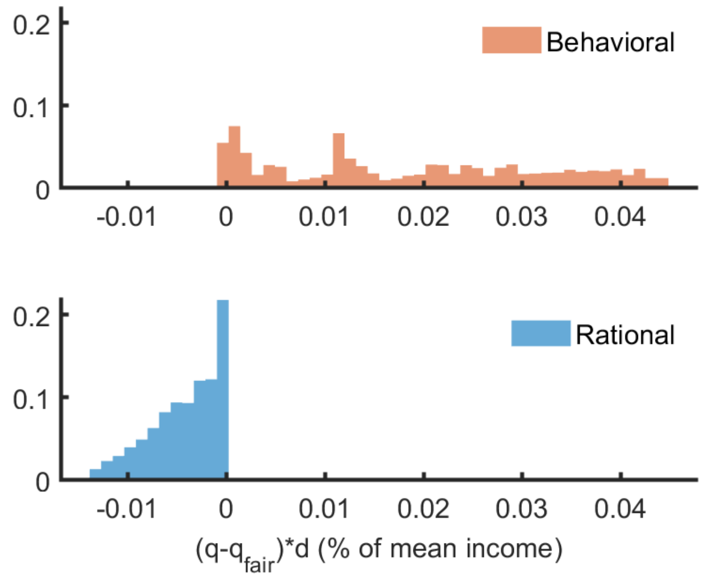


Figure 3: Distribution of Cross-Subsidization (PDF)

librium 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 behavioral households that choose not to file for bankruptcy at period t 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% if these borrowers were informed. Over-optimistic expectations of future income thus generates both a greater desire to borrow and a willingness to roll-over loans rather than to default right away.

We measure overborrowing as the 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 2.8% too much debt relative to their rational selves in the same state facing the same prices.

4.2 Decomposition

The borrowing and default decisions of behavioral consumers are shaped by their over-optimism, the higher risk of their income process, and by the partial pooling of types. To decompose the contribution of these factors, we simulate three counterfactual economies. Each counterfactual is populated solely by one type of household, with and without over-optimistic beliefs, and with different income processes (see Table 4).

These experiments show that the direct effects of the differences in transitory income risk between realists and behavioral households are modest. The first two columns of Table 4 report the outcome for an economy populated solely by agents with correct, rational beliefs. Column 1 corresponds to the low-risk income process of realists, while column 2 reports the high risk income process of behavioral agents. Since these economies are populated by one type, not only are expectations correct but there is also no cross-subsidization and borrowing interest rates are actuarially fair. While higher negative transitory income risk pushes up filings, the quantitative impact is modest (0.02 pp, roughly a 4% rise). Moreover, there is little impact on the average debt-to-income ratio. The fraction of total borrowers, bankruptcy filings per borrower, and the debt-to-earnings ratio of defaulters also remain similar.

A comparison of the second and third columns in Table 4 shows the large effect of over-optimistic expectations. In both columns, households have the high-risk income process, with Column 3 reporting the case where households are over-optimistic and make financial mistakes. The impact on debt is substantial, as over-optimism results in an increase in the debt-to-earnings ratio from 6.4% (column 2) to 8.2% (column 3).[24]

The observed impact of filings is more modest, as filings are roughly 10% higher in the over-optimist economy (0.51% versus 0.46%). In part, this reflects that over-optimists file for bankruptcy too late. If suddenly made aware, an additional 0.3% of agents would file for bankruptcy—nearly a 60% increase in filings.

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 rational agents would choose to default. This results in *lower* average interest rates (compare columns 3 and 2 in

[24]Table 4 compares different debt-to-income ratios across different equilibria, which is different from our 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.

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

Income Process	Better Risk	Worse Risk	Worse Risk	Worse Risk
Beliefs	Realistic	Realistic	Over-optimistic	Over-optimistic
Pooling	Not pooled	Not pooled	Not pooled	Pooled
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%	11.1%
Total borrowers	0.20	0.20	0.23	0.23
Filings per borrower	2.25%	2.29%	2.18%	2.27%
Debt-to-earnings of defaulters	321%	316%	314%	343%
Overborrowing	-	-	3%	2.80%
Filing too late	-	-	0.3%	0.29%

Note: The counterfactuals summarized in this table differ along three dimensions: (1) The transitory income process can either be *better* (the rational's process) or *worse* (the behavioral's process). (2) Beliefs can either be *realistic* or *over-optimistic*. (3) Agents can either populate an economy alone—*not pooled*—and receive actuarially fair prices or be *pooled* with 83% realists.

Table 4). This is a consequence of two effects: First, there are 15% more borrowers when beliefs are over-optimistic (0.23 vs. 0.2) 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. This commitment-to-repay effect decreases interest rates.

The final column of Table 4 reports the outcomes for behavioral households in our benchmark economy. Comparing columns 3 and 4 separates out the effect of cross-subsidized interest rates as the behavioral households in column 4 account for only 17% of the population. 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 loss, given the default of borrowers. The cross-subsidized interest rate schedules change the distribution of debt holdings as low debts are cheaper to repay if rolled over. This also means that 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 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 higher loss given default. On average, the interest rate for behavioral borrowers *increases* by 131 basis points despite their receiving subsidized loan contracts.

4.3 Fraction of Behavioral Agents

Since behavioral consumers play a central role in our analysis, it is natural to ask what happens as one varies their share in the economy. Table 5 reports aggregate and individual outcomes as one varies the fraction of behavioral agents in the economy from zero

Table 5: 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%

to our calibrated value of 17% and for values up to 100%.[25]

Average outcomes are driven by changes in individual behavior and changes in the composition of borrowers. Although both types of agents hold less debt and default less in an economy with more behavioral agents, the composition effect dominates: the average debt-to-income ratio and average bankruptcies increase in λ because there are more behavioral borrowers that hold more debt and default more often. However, the composition effect does not dominate for average interest rates, which decline as the fraction of behavioral agents (λ) rises. Although behavioral agents pay higher interest rates for any given fraction λ, both agents individually pay lower average rates as the fraction λ rises. These individual interest rate effects dominate the composition effect.

[25] In this analysis, we compare economies with different λ, holding fixed all other parameters; i.e., we do not re-calibrate to match aggregate earnings dynamics as the fraction of risky people increases.

4.4 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 arguments of Hynes (2004) that behavioral consumers could under-borrow since they place too high a probability on repaying debt. We find that behavioral agents over-estimate 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 between the types discussed in 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 less than 0.002% (in consumption equivalence). This loss combines both the effect of cross-subsidization as well as 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.[26] In this section, we use our framework to investigate several policy interventions that could alleviate financial mistakes. Behavioral borrowers make two types of mistakes—they borrow too much and they file too late. We thus analyze two policies aimed at limiting borrowing—a tax on borrowing 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.[27] We also consider a policy, which we call financial literacy education, that informs people of their type and thereby eliminates financial mistakes. The results of these experiments are summarized in Table 6.

5.1 Higher Borrowing Costs

A central argument for regulating consumer credit is to preempt overborrowing. This motivates policies aimed at reducing the incentives 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 an increase in the costs of lending. Consequently, if individuals overborrow, a higher cost of lending may be beneficial if it discourages "mistaken" borrowing. On the other hand, there is a clear deadweight cost attached to the higher cost of lending. Moreover, a higher borrowing cost affects everyone, including rational people who use credit correctly.

Our borrowing cost experiment increases the risk-free lending rate by one percentage point, from 6.3% in the benchmark to 7.3%. Higher borrowing costs reduce borrowing and bankruptcy filings (see the second column in Table 6). If a policymaker's objective were to reduce debt and bankruptcies, then this policy could be considered a success.[28]

[26] 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."

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

[28] In the popular debate, high debt and many defaults are a common indicator of lacking regulation.

Table 6: Policy Experiments

Parameter	(1) Benchmark	(2) Borrow Cost ↑ $\tau = 7.3\%$	(3) Default Cost ↓ $\gamma = 30\%$	(4) Financial Literacy	(5) Debt-to-income $\leq 100\%$	(6) Debt-to-income $\leq 100\%$ if $s < 0.8$
Debt-to-income						
Rational	6.37%	5.14%	4.92%	6.38%	4.74%	5.33%
Behavioral	8.22%	6.72%	6.35%	6.39%	6.21%	6.79%
Average	6.67%	5.40%	5.15%	6.38%	4.98%	5.57%
Bankruptcy filings						
Rational	0.44%	0.42%	0.70%	0.44%	0.42%	0.43%
Behavioral	0.53%	0.51%	0.84%	0.46%	0.50%	0.51%
Average	0.45%	0.44%	0.72%	0.44%	0.43%	0.44%
Average interest rates						
Rational	10.40%	11.84%	13.09%	10.59%	9.61%	10.06%
Behavioral	11.12%	12.69%	14.45%	10.38%	10.10%	10.50%
Average	10.55%	12.01%	13.37%	10.55%	9.71%	10.15%
Paternalistic welfare						
Rational		-0.28%	0.21%	0.02%	-0.31%	-0.21%
Behavioral		-0.29%	0.23%	-0.09%	-0.31%	-0.25%
Average		-0.28%	0.22%	0.01%	-0.31%	-0.22%
Financial mistakes						
Filing too late	0.29%	0.11%	0.20%	0.00%	0.03%	0.08%
Overborrowing	2.80%	4.53%	7.88%	0.00%	1.67%	2.33%

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

However, both types of agents dislike higher borrowing costs. It is not surprising that rational consumers, who do not make financial mistakes, are made worse off by more expensive credit. What is surprising is that the welfare losses are larger for over-optimists than for rationals. The reason is that even though *borrowing* declines, *overborrowing* actually increases. Relative to their informed selves, behavioral agents reduce their borrowing too little in response to higher borrowing interest rates and, thus, make larger mistakes. These mistakes reduce behavioral agents' welfare more than that of rational agents. This policy does, however, reduce mistakes in the timing of filings as the fraction of behaviorals filing too late declines from 0.29% in the benchmark economy to 0.11%.[29] However, this benefit is not enough to outweigh its direct costs.

5.2 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 6 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 agents. The rise in default rates lead lenders to increase their interest rate schedules, and thus tightens the endogenous borrowing constraints. As a result, average borrowing interest rates jump to 13.37%. Due to higher borrowing costs, households cut their debt-to-income ratio nearly in half.

The direct and indirect effects of reduced default costs lower our measure of filing too late by almost 30%. Although this aspect of financial mistakes by over-optimists declines, overborrowing rises steeply from 2.8% to 7.9%. The reason is simple: while borrowing declines, it does not decline as fast as it would for informed borrowers.

Unlike a policy that targets a higher cost of borrowing, lowering the cost of default increases welfare (see Table 6). However, since rational consumers benefit equally, these gains are not driven by fewer mistakes by behavioral borrowers. Instead, in our calibrated model, 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)).

[29] This decline in filing too late does not lead to higher filing rates. Rather, behavioral agents file earlier since, with higher borrowing costs, rolling over debt is more expensive.

5.3 Financial Literacy Education

Neither of the above policies reduces both types of financial mistakes. Thus, we conduct an experiment where we remove the reason behavioral households make financial mistakes: over-optimism regarding their future transitory income risk. Under "financial literacy education," we educate behavioral agents about their true risks so as to eliminate overborrowing and filing too late. In this counterfactual, all agents know their true income process. We assume that behavioral agents become perfectly identified to themselves *and* to lenders. As before, we adopt a paternalistic welfare measure.[30]

While this policy provides a useful counterfactual to assess the effectiveness of addressing incorrect beliefs, such a policy could not be implemented perfectly in practice. In our environment, neither consumers nor lenders know who is behavioral. Thus, introducing an omniscient government that knows each consumer's type is a stark assumption. As we abstract from implementation challenges, our findings provide an upper bound for policies that increase awareness of behavioral biases.

As can be seen from column (4) of Table 6, perfectly informing behavioral agents about their income process has two opposing effects on behavioral agents. First, they no longer make financial mistakes as they now have correct expectations of their future income.[31] As a consequence of learning their true income process, behavioral agents realize that they are poorer than expected and reduce their borrowing from a debt-to-income ratio of 8.22% to 6.39%. This debt-to-income ratio nearly coincides with that of realists. Hence, behavioral agents are less likely to find themselves with large debts and low income realizations. Consequently, they file for bankruptcy less often. Lower amounts of debt and fewer defaults lead to lower *average realized* interest rates for behavioral borrowers.

At a first glance, financial literacy education appears to be a successful policy: imposing correct expectations reduces the debt and filings of behavioral consumers and eliminates mistakes. Yet, the welfare of behavioral agents *declines*. What causes this counter-intuitive result? Financial literacy education also ends cross-subsidization since behavioral borrowers are no longer (partially) pooled with rationals. In the benchmark, the partial pooling of behavioral borrowers with rationals results in their being cross-

[30]Due to the nature of over-optimism, this policy directly reduces the perceived welfare of behavioral agents by lowering their expectations.

[31]For simplicity, we continue to refer to these (now) informed poorer agents as "behavioral".

subsidized through lower interest rate schedules.[32] In terms of welfare, the loss of cross-subsidization dominates the gains from eliminating financial mistakes and behavioral agents end up nearly 0.1% worse off (in consumption equivalence units).

For realists, the policy has the opposite result as it leads to higher welfare. Although the education campaign does not directly affect their actions, the policy removes cross-subsidization which lowers the interest rate *schedules* they are quoted. Rational agents react by borrowing slightly more, which leads to slightly higher *average realized* interest rates in equilibrium. As a result, this policy provides realists with a small increase in welfare of 0.02% consumption equivalence units.

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).[33] 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 a borrower's ability to repay by taking their income into account.[34]

To implement DTI limits in the model, we use current persistent income $e \times z$ as our denominator. We abstract from transitory shocks, as they contain no information about future income realizations when the debt becomes due. Furthermore, in practice, lenders may have little information about contemporaneous temporary income shocks. The debt-to-income ratio relates current borrowing to income: $q(\cdot)d'/(ez)$.[35]

We report the effects of a relatively loose debt-to-income limit of 100% in column (5) of Table 6. 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.

[32] Higher interest rate *schedules* are not at odds with lower *average realized* interest rates. For a given—higher—interest rate schedule, behavioral agents pick lower amounts of debt in equilibrium, leading to lower realized interest rates.

[33] We discuss an alternative limit on debt payments relative to income in Appendix B.

[34] 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.

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

Fewer bankruptcies lead to lower-risk premia and consequently drive down average borrowing interest rates. The average borrowing interest rate is 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 1.67%. Despite these positive effects, the total welfare effects are negative. Agents lose 0.31% in consumption equivalence units under a debt-to-income limit. The negative welfare effect of constraining agents' borrowing decisions dominates the benefit of reducing financial mistakes. To reduce the adverse effects of a DTI limit and target these policies at behavioral agents, the next section explores DTI limits that only apply to agents with low type scores.

6 Score-Dependent Consumer Protection Policies

Introducing borrowing limits for all agents can reduce financial mistakes but also 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 only applies 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).[36] 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 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.

[36] Policies targeted at households above or below a threshold are common. For example, Mitman (2016) analyzes the 2009 HARP, which effectively gave an interest rate subsidy to borrowers with loan-to-value ratios between 80 and 125%.

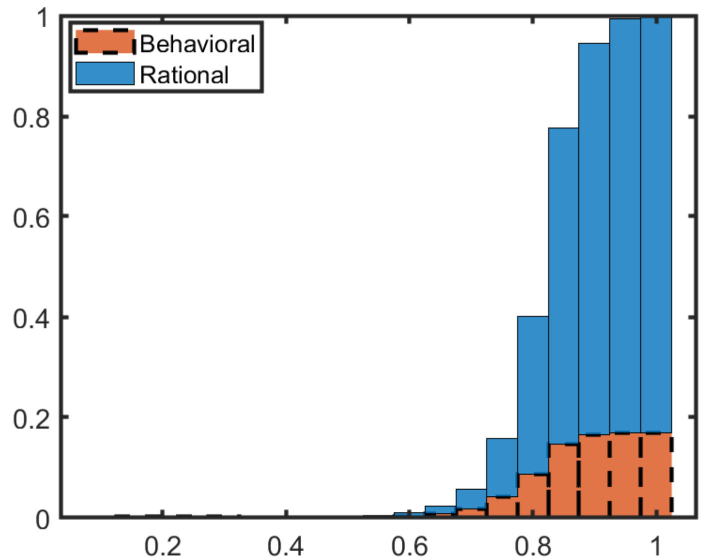


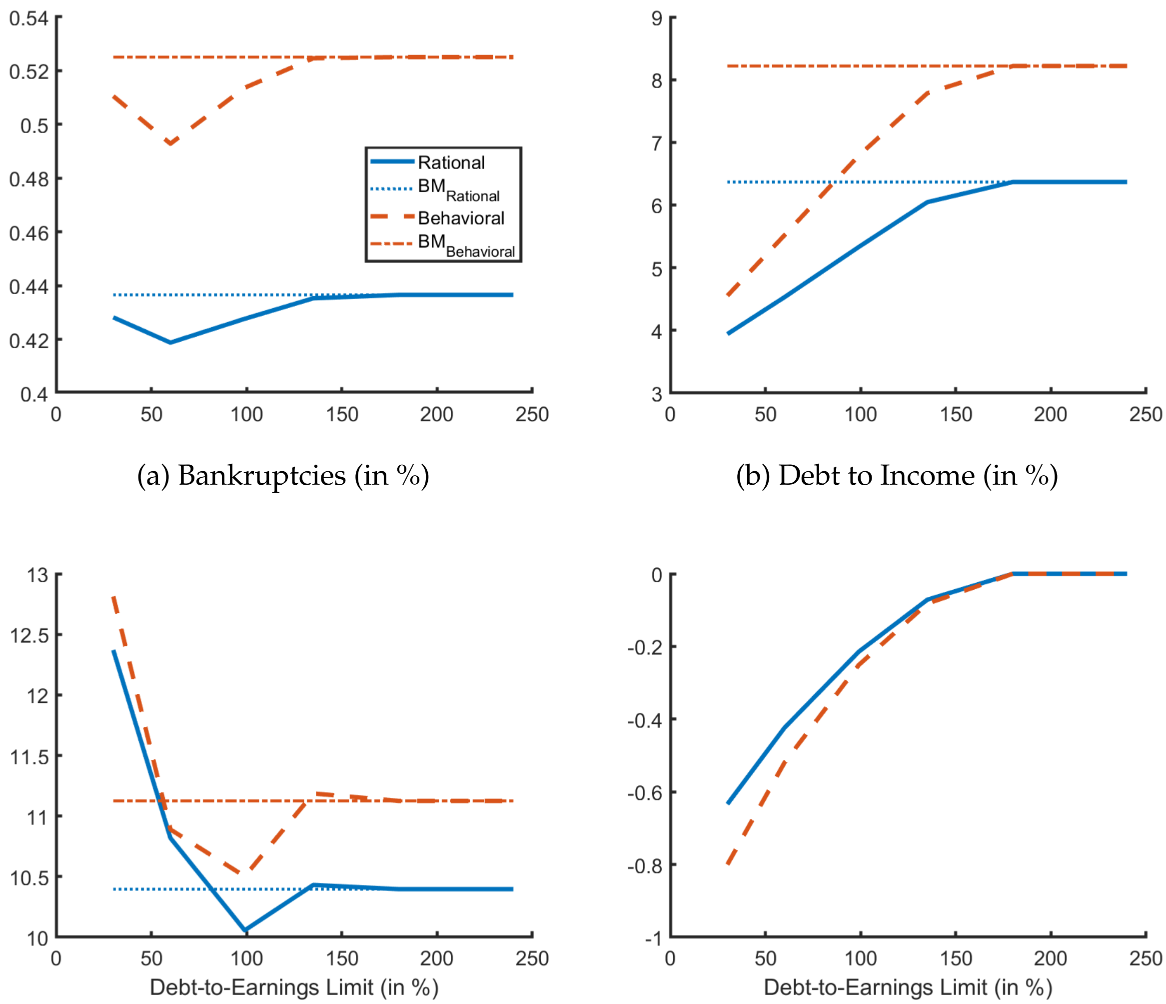
Figure 4: CDF of type scores, split by type. The values are in Table 10 in Appendix D.

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, albeit less than untargeted limits, due to the costs of restricting access to credit.

To examine the impact of varying the debt-to-income limit, we fix the type-score threshold below which the policy applies at 0.8. In equilibrium, this affects about 16% of the population. Although behavioral borrowers have lower type scores on average, roughly three-quarters of those affected are rational agents.

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 (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 debt-to-income limits that are more binding also lead to lower filing rates? Initially, yes, as panel (a) shows. This is consistent with the effect advocates for regulation have in mind when arguing that preventing people from "borrowing too much" will



(a) Bankruptcies (in %)

(b) Debt to Income (in %)

(c) Interest Rates (in %)

(d) Welfare (in % CEV)

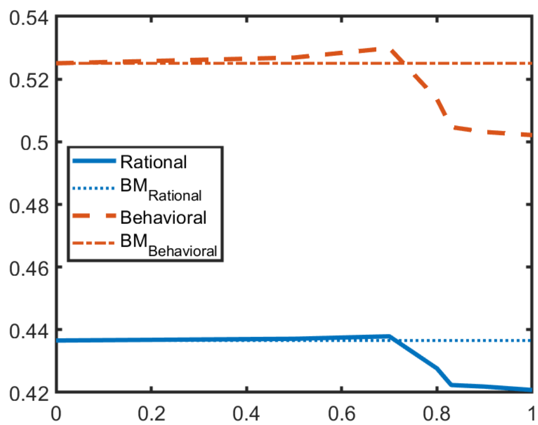
Figure 5: Debt-to-Income Limits at Type Score 0.8

reduce bankruptcies. However, at some point, further reductions in DTI limits cause filings to increase. The reason is that a low limit on debt prevents borrowing by households that are good credit risks but experience temporary bad shocks (e.g., an expense shock). Moreover, for large shocks, some households that could have borrowed (and repaid) without declaring bankruptcy with high DTI limits are unable to borrow enough with low DTI limits and, thus, are forced into bankruptcy. Since this constrains more people at lower DTI limits, 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 low DTIs drive average interest rates above the benchmark level.

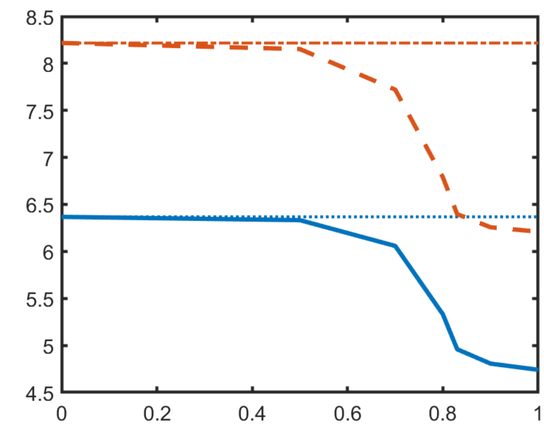
From a welfare perspective, stricter debt-to-income limits are not good policy, even in the range where filings decrease, as average welfare (in consumption equivalence terms) declines. These welfare effects reflect the costs of limiting access to credit to smooth shocks to income, and the welfare declines are larger for behavioral than for rational households. The larger adverse impact on behavioral borrowers from tight borrowing limits is simple: since they are more likely to experience negative transitory income shocks, they are more likely to borrow to smooth consumption. Thus, even though this policy lowers debt and, potentially, bankruptcies, it lowers rather than increases 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 reduced the most, and we vary the type-score threshold from 0 to 1 (see Figure 6). Note that a threshold of 1 corresponds to column (5) in Table 6. 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.

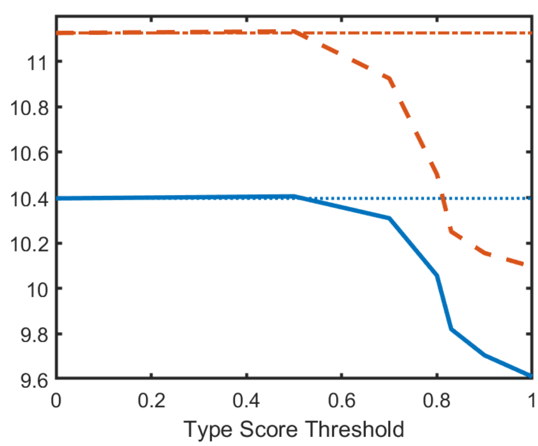
Our experiment suggests that while making regulations and restrictions dependent on borrowers' type scores so as to target behavioral borrowers is intuitively attractive, it does not eliminate the adverse effects of limiting debt. Limits on borrowing tend to bind and restrict an individual's borrowing exactly when the need to borrow is highest.



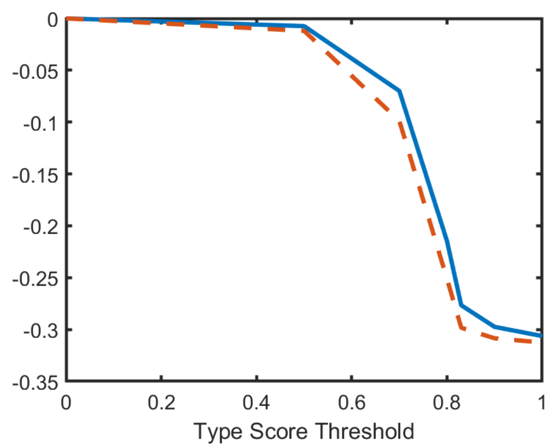
(a) Bankruptcies (in %)



(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

Moreover, type-dependent policies face the challenge that adverse transitory income shocks that necessitate borrowing also lower a borrower's type score. If the latter triggers an additional restriction on borrowing, then policy will tend to harm borrowers (regardless of their type) and lower welfare.

7 Conclusion

In this paper, we quantitatively analyze consumer credit markets with behavioral consumers and default. We find that 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 that significant spillovers in credit markets can arise in equilibrium between rational and behavioral borrowers. Central to this insight is that, in a world where lender's 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. This means they borrow too much and default too late. To address these financial mistakes, we explore several potential credit regulations, including a tax on borrowing, making default less costly, financial literacy education where we inform consumers and lenders about their true types as well as limits on borrowing. Our findings pose a cautionary tale for the effectiveness of consumer financial regulation, as most of the policies we consider are either 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 specific regulatory policies, a clear lesson from our paper is that regulation likely affects the cross-subsidization implicit in defaults and that this has welfare consequences.

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

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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 7 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 7).

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).

Table 7: Educational attainment and total income across financial literacy

The 2016 SCF also contains a question (X7650) that asks the respondent whether their total income in 2015 was unusually high, low, or normal compared to their expectation during a "normal" year. Table 8 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 financially illiterate households. 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 $\text{Prob}(\eta) = [0.1, 0.8, 0.1]$, 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 $\text{Prob}(\eta_1) = (1-\lambda)\text{Prob}^R(\eta_1) +$

Correctly	Fraction	Fraction with income		
answered questions	of households	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

Table 8: Unusual income across financial literacy

$\lambda\psi\text{Prob}^R(\eta_1) = \text{Prob}(\eta_1)(1 - \lambda + \lambda\psi)^{-1}$. Then, $\text{Prob}^B(\eta_1) = \psi\text{Prob}^R(\eta_1)$ and $\text{Prob}^T(\eta_3) = 1 - \text{Prob}^T(\eta_2) - \text{Prob}^T(\eta_1)$ for $T = \{B, R\}$. See Table 1 for the resulting values.

B 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 repay 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: $(1 - q(\cdot))d'/(ez)$.

B.1 Untargeted DSR Limits

Table 9 replicates Table 6 and reports a DSR limit of 45% in column (6). In contrast to a debt-to-income limit, DSR limits bind more strongly for riskier loans. Typically, riskier loans carry higher interest rates and are thus 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 (6) in Table 9 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 is more effective at reducing overborrowing than a DTI limit (0.21% vs. 1.67%). However, agents suffer from borrowing restrictions and the total welfare effect is negative. Agents lose 0.03% in consumption equivalence units.

B.2 Targeted DSR Limits

In line with Section 6, we also investigate DSR limits when they only apply 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 type-dependent DSR limits have smaller negative welfare effects whilst maintaining low equilibrium interest rates.

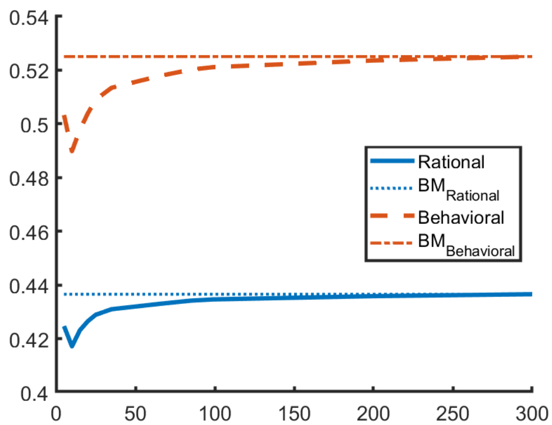
Figure 7 depicts what happens to bankruptcy filings, debt, interest rates, and welfare as the DSR limit moves from from 0 to 300%. The type-score threshold is fixed at 0.8 and about 40% of consumers are affected (see Figure 4). Loose limits (roughly 300% and higher) are nonbinding and hence debt, filings, 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 even for very tight DSR limits. One reason is that unconstrained safe borrowers can use debt to smooth adverse shocks. Hence, there is a smaller selection effect that drives up interest rates when DSR limits are tight. Second, DSR limits preclude high interest rate loans, mechanically driving down average interest rates.

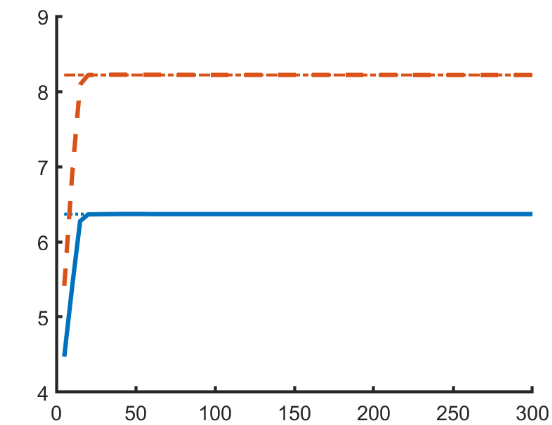
Table 9: Policy Experiments with DSR

Parameter	(1) Benchmark	(2) Borrow Cost ↗ $\tau = 7.3\%$	(3) Default Cost ↘ $\gamma = 30\%$	(4) Financial Literacy	(5) Debt-to-income $\leq 100\%$	(6) Debt Service Ratio $\leq 45\%$
Debt-to-income						
Rational	6.37%	5.14%	4.92%	6.38%	4.74%	6.23%
Behavioral	8.22%	6.72%	6.35%	6.39%	6.21%	8.05%
Average	6.67%	5.40%	5.15%	6.38%	4.98%	6.53%
Bankruptcy filings						
Rational	0.44%	0.42%	0.70%	0.44%	0.42%	0.41%
Behavioral	0.53%	0.51%	0.84%	0.46%	0.50%	0.49%
Average	0.45%	0.44%	0.72%	0.44%	0.43%	0.43%
Average interest rates						
Rational	10.40%	11.84%	13.09%	10.59%	9.61%	8.55%
Behavioral	11.12%	12.69%	14.45%	10.38%	10.10%	8.57%
Average	10.55%	12.01%	13.37%	10.55%	9.71%	8.56%
Paternalistic welfare						
Rational		–0.28%	0.21%	0.02%	–0.31%	–0.03%
Behavioral		–0.29%	0.23%	–0.09%	–0.31%	–0.03%
Average		–0.28%	0.22%	0.01%	–0.31%	–0.03%
Financial mistakes						
Filing too late	0.29%	0.11%	0.20%	0.00%	0.03%	0.13%
Overborrowing	2.80%	4.53%	7.88%	0.00%	1.67%	0.21%

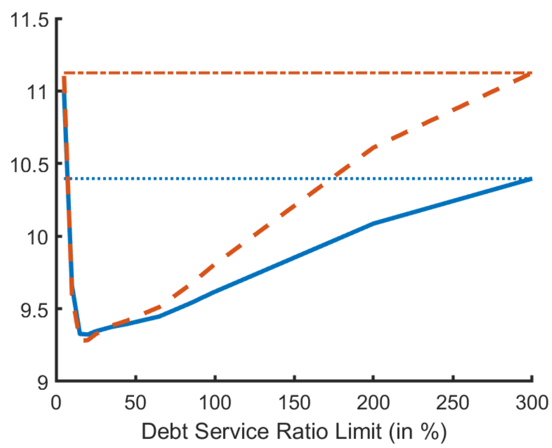
Note: Welfare is expressed as the consumption equivalence variation relative to the benchmark (BM).



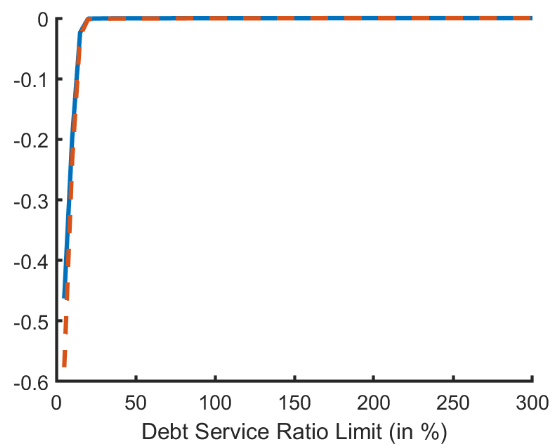
(a) Bankruptcies (in %)



(b) Debt to Income (in %)



(c) Interest Rates (in %)



(d) Welfare (in % CEV)

Figure 7: Debt Service Ratio Limits at Type Score 0.8

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 (6) in Table 9. Overall, Figure 8 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.

C Details of Borrowing Limit Regulation

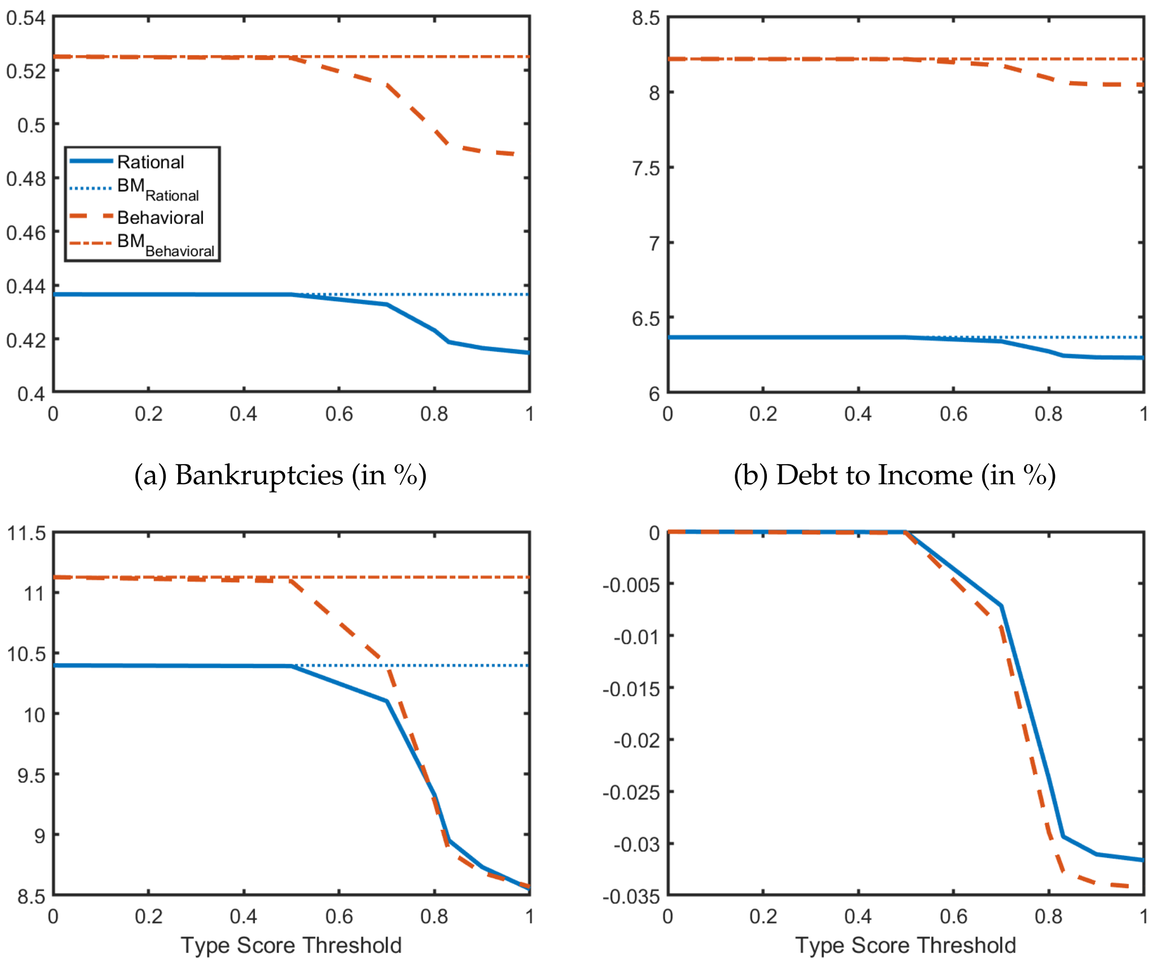
Here we provide the equations behind the policies considered in Sections 5.4 and 6. *Debt-to-income limits* are defined as follows.

$$q^b(d', z, j, s) = \begin{cases} q^{ub}(d', z, j, s) & \text{if } q^{ub}(\cdot)d'/(ez) \leq B(s) \\ 0 & \text{otherwise.} \end{cases} \tag{13}$$

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 that applies to all scores, s, below a threshold, $\overline{s}$, while consumers above the threshold face no limit. In other words, we set

$$B(s) = \begin{cases} \overline{B} & \text{if } s < \overline{s} \\ \infty & \text{if } s \geq \overline{s}. \end{cases} \tag{14}$$

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



(a) Bankruptcies (in %)

(b) Debt to Income (in %)

(c) Interest Rates (in %)

(d) Welfare (in % CEV)

Figure 8: Debt Service Ratio Limit of 45% With Changing Type-Score Thresholds

than a conventional measure of debt). Debt as it is conventionally defined corresponds to qd'. 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.

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:

$$q^b(d', z, j, s) = \begin{cases} q^{ub}(d', z, j, s) & \text{if } (1 - q^{ub}(\cdot))d'/(ez) \leq DSR(s) \\ 0 & \text{otherwise.} \end{cases} \tag{15}$$

As above, q^{ub} is the unrestricted borrowing bond price. Putting a limit on the DSR means that as soon as the interest payment is too high relative to income (defined as ez as before), borrowing is no longer possible, thus, q is set to zero in such a case. As above, the limit itself depends on the type score.

$$DSR(s) = \begin{cases} \overline{DSR} & \text{if } s < \bar{s} \\ \infty & \text{if } s \geq \bar{s}. \end{cases} \tag{16}$$

D Ergodic Distribution of Type Scores

Table 10: Type-Score Distribution in Benchmark Calibration

	Frequency			Cumulative		
Score	Rational	Behavioral	% Behavioral	Rational	Behavioral	% Behavioral
0.10	0.00%	0.00%	100.00%	0.00%	0.00%	100.00%
0.15	0.00%	0.00%	81.32%	0.00%	0.00%	81.84%
0.20	0.00%	0.00%	72.29%	0.00%	0.00%	73.61%
0.25	0.00%	0.00%	63.13%	0.00%	0.00%	65.04%
0.30	0.00%	0.00%	57.78%	0.00%	0.00%	59.62%
0.35	0.00%	0.00%	54.52%	0.00%	0.00%	55.99%
0.40	0.01%	0.01%	51.57%	0.01%	0.01%	52.99%
0.45	0.02%	0.02%	46.52%	0.03%	0.03%	48.73%
0.50	0.05%	0.04%	43.14%	0.08%	0.07%	45.23%
0.55	0.15%	0.10%	38.86%	0.23%	0.16%	41.29%
0.60	0.37%	0.20%	35.44%	0.60%	0.37%	37.82%
0.65	1.00%	0.45%	31.27%	1.60%	0.82%	33.89%
0.70	2.43%	0.94%	27.95%	4.03%	1.76%	30.44%
0.75	7.72%	2.36%	23.44%	11.75%	4.13%	25.99%
0.80	19.66%	4.55%	18.79%	31.40%	8.67%	21.64%
0.85	31.62%	5.94%	15.81%	63.02%	14.61%	18.82%
0.90	14.95%	1.95%	11.54%	77.98%	16.56%	17.52%
0.95	4.44%	0.40%	8.26%	82.42%	16.96%	17.07%
1.00	0.58%	0.04%	5.85%	83.00%	17.00%	17.00%