Consumer Credit with Over-Optimistic Borrowers*

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Abstract

We quantitatively analyze consumer credit markets with behavioral consumers and default. Our model incorporates over-optimistic and rational borrower types into a standard incomplete markets model with consumer bankruptcy. Lenders price credit endogenously, forming beliefs – type scores – about borrowers' types. Since over-optimistic borrowers incorrectly believe they have rational beliefs, lenders do not need to take strategic behavior into account when updating type scores. We find that the partial pooling of over-optimistic with rational borrowers results in spill-overs across types via interest rates, with over-optimists being cross-subsidized by rational consumers who have lower default rates. Due to overestimating their ability to repay, over-optimists make mistakes – they borrow too much and file too late. We evaluate several policies to address these frictions: reducing the cost of default, increasing borrowing cost, and financial literacy education. While several policies do lower debt and filings, they are not successful at reducing financial mistakes and thus are not welfare improving. Financial literacy education backfires in that it hurts over-optimists by removing cross-subsidization. Score-dependent policies are not faring much better.

Keywords: Consumer Credit, Credit Card Debt, Endogenous Financial Contracts, Overoptimism, Bankruptcy, Financial Literacy, Financial Regulation, Type Scoring, Cross-Subsidization

JEL Classifications: E21, E49, G18, K35

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1 Introduction

The rise in consumer credit and the number of household filing for bankruptcy has renewed debate over consumer financial protection. Much of this debate centers around whether borrowers' cognitive biases create a need for regulation that limit harmful borrowing decisions (Bar-Gill and Warren 2008; Campbell 2016). Proponents of consumer finance regulations often argue (some) consumers over-borrow due to behavioral biases, or that less-sophisticated borrowers are exploited by sophisticated lenders. This has resulted in some calling for regulations targeted at preventing households from over-borrowing and ending up "trapped in debt."[1] Opponents of additional financial regulations often point towards the adverse effects of regulations on rational borrowers who face higher borrowing costs and reduced access to credit as a results of costs arising from regulations (e.g. Zywicki (2013)). Although this debate is far from settled, the 2008 Financial Crisis helped crystallize support for significant 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 both "rational" and "behavioural" households to analyze consumer financial regulation.[3] Given that much of the debate over regulation focuses on products such as 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 an 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 behavioural borrowers is not directly observable. As a result, lenders price credit endogenously based on beliefs about a borrower's type. We study how the updating of these beliefs over a borrower's life impacts the interest rates at which they borrow, and show that spill-overs between rational and over-optimistic borrowers naturally arise.

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

[1] e.g., see Senator Chris Dodd, U.S. Senate, Congressional Record, 155, S5314 (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-rationally in consumer finance is debated in the literature. Telyukova and Wright (2008) and Telyukova (2013), for example, argue the credit card debt puzzle can be largely explained by households' need for liquidity. Our paper is not intended to settle this debate, but examines the trade-offs of alternative regulations if over-optimistic consumers exist.

default decisions of different types.[4] We show that over-optimistic consumers make 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 introduce behavioral consumers into our model by assuming they are 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 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 behavioural 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 risk they face. While conceptually these are distinct features (and we decompose results for each channel), in practice they often come hand in hand. As we document, financially illiterate respondents in the SCF also report being surprised by low income realizations more often. This pattern of being more exposed to shocks co-existing with over-optimism has also been documented among 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 is an incomplete-market economy with bankruptcy populated by finitely lived heterogeneous agents subject to idiosyncratic earnings and expenditures (i.e. "expense shocks"). Households decide on how much to borrow or save, and whether to file for bankruptcy. There are two types of households: realists who hold correct beliefs

[4](Campbell 2016) also emphasizes the need for models where both types of agents meaningfully inter.

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

[6]An alternative interpretation is they have limited financial literacy in that they 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 which bias is most important or the fraction of consumers in the US whose behavior is not rational.

over the uncertainty they face, and over-optimists that think of themselves as realists (and – conditional on their state – behave as realists) but actually face systematically higher risk. If households do not default, they can borrow or save in a one-period bond that is priced in a perfectly 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 realist. Instead, financial intermediaries observe income realizations and form beliefs on the probability that a household is a realist. We refer to these beliefs as type scores. 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 with 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 her idiosyncratic uncertainty. The model thus gives rise to a tractable theory of type scoring.

We find that behavioral consumers have a significant impact on the observed aggregates in our quantitative model calibrated to the US economy. Even though they make up only 17% of the population, the economy-wide 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. A decomposition analysis shows that most of this is driven by the incorrect beliefs of the behavioral agents, rather than the assumption that they also face more risks. We find that if the fraction of over-optimists rises in our economy, both types borrow less and default less at an individual level. However, aggregate debt and aggregate bankruptcies increase due to a composition effect: when increasing the fraction of over-optimists, the economy is composed of more risky households that borrow and default more.

Zooming in on the behavioral consumers, we show that they make mistakes. We define mistakes as behavior that is different from what a fully informed version of themselves would do, holding equilibrium prices constant. We find that they over-borrow and file too late. Quantitatively, if suddenly made aware, they would borrow 3% less and an additional 0.3% would file for bankruptcy. This arises because over-optimistic consumers have too optimistic views about the future and hence, rather than defaulting right away, they expect to repay their debt in the future. However, over-optimists are systematically surprised by future bad realizations, and end up unable to get out of debt. Thus, it seems there is room for policy intervention. However, there is also a force in the model that works in favor of behavioral consumers. The equilibrium allocation in our model generates spill-overs between rational and over-optimistic borrowers in the form of cross-subsidization through the interest rate. Since over-optimists default more often, cross-subsidization goes from rational to behavioral consumers. Any form of regulation that reduces the amount of cross-subsidization may thus hurt behavioral consumers.

We analyze several potential policy interventions that might address the mistakes that behavioral consumers make and explore how they affect behavior and welfare of both types of agents.[7] First, we reduce the cost of default, inducing over-optimistic people to default earlier. Second, we explore the implications of making borrowing more costly through increased regulatory requirements or a proportional transactions tax. This should reduce over-borrowing. Third, we investigate "financial literacy education" where we inform people about their true type, inducing them to internalize the true probabilities into their beliefs.

These policy experiments provide interesting insights into the winners and losers from credit regulation. First, reducing default costs indeed reduces mistakes in that filing too late declines substantially among the behavioral consumers. They also benefit in welfare terms. The reason seems orthogonal to the mistakes though, as rational consumers equally benefit. Thus, overall default costs were simply too high from a welfare point of view in our calibrated model. Second, increasing transactions costs does not help address the over-borrowing problem. While behavioral consumers do lower their debt substantially, it does not decline by enough compared to what a fully aware consumer would do. Thus, our measure of over-borrowing even goes up. Welfare declines for both types of consumers. Third, financial literacy education backfires in the sense that precisely over-optimists will be made worse off. While this policy eliminates mistakes completely (which in itself is unambiguously welfare improving), the policy also eliminates any scope for cross-subsidization. Losing such cross-subsidization dominates the elimination of mistakes so that behavioral consumers are worse off. Rational people, on the other hand, benefit from the policy because they are no longer pooled with the high-risk over-optimists.

Given that general policies that apply to all agents fail increasing welfare, we now ex-

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

plore whether more targeted policies do better. Since in our set-up targeting behavioral people is impossible, we explore targeting by score instead. Specifically, we analyze debt-to-income and debt-service ratio (DSR) limits targeted at agents with a low type score (and hence a high probability of being behavioral). We find that such limits lower both borrowing and default which is typically a prime objectives of regulating the credit market. However, they also tend to lower welfare due to restricted access to credit for some. Thus, simply measuring the success of such policies by their effect on debt and default will be misleading.

Our contribution to the literature is three-fold. First, despite broad evidence on behavioral traits in consumers, surprisingly little work has incorporated behavioural borrowers into quantitative models of consumer debt and default. 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) – and thus conceptually quite different from the over-optimists considered in our paper. Laibson, Tobacman, and Repetto (2000) and Nakajima (2012) are positive analyses not concerned with policy implications. The only other paper that analyzes the policy implications of introducing behavioral consumers into a consumer bankruptcy model is Nakajima (2017), which also finds that behavioral and rational consumers can disagree about the desirability of reforms. However, there are no direct spillover effects in that model as rational and behavioral consumers simply co-exist without any interaction. This is quite different from our set-up where the two types affect each other both through the interest rate and the type-score updating.

Second, we connect 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 under some conditions, behavioral (and naive) debtors end up paying more for the same product than (informed) rational debtors. The extra fees paid by the 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 that underestimate their future impatience. These borrowers back-load repayments and thus incur penalties that they did not anticipate ex-ante. However, none of these papers incorporate default in equilibrium. This is potentially important both because risk-based pricing is a justification for higher pricing for some consumers, and since high default rates are cited as a major concern in the policy debate. Further, as we will show in this paper, 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 the risk of default, our structure differs from one common definition of predatory lending. Bond, Musto, and Yilmaz (2009) define a *predatory loan* as one which a borrower would decline if they had the same information as the lender. Depending on each household's type score, lenders in our model pools borrowers with correct beliefs about future default risk with borrowers who incorrectly share the same beliefs. But – contrary to Bond, Musto, and Yilmaz (2009) – over-optimists are aware of and agree with their type score as it is simply a function of realized past shocks. They are ignorant about their fundamentally higher risk and just think of themselves as being unlucky and thus pooled with worse risks. As a result, they agree to the loan contract offered to them. Even more strikingly, if one was to resolve their ignorance, over-optimists would understand that their loan contracts have been subsidized by rational types and be more than happy to accept those contracts.

Our third contribution is a very tractable model of type-scoring in consumer credit markets. Our approach gets around a technical issue the consumer finance literature on credit scoring has struggled with (Chatterjee, Corbae, and Rios-Rull 2008; Chatterjee et al. 2020; Corbae and Glover 2018; Sanchez 2017; Elul and Gottardi 2015; Athreya, Tam, and Young 2012). To keep the model tractable, Chatterjee et al. (2020) adds extreme-value shocks to the household's utility function. Since these shocks are unobservable to the financial industry, they introduce noise that renders perfect screening contracts impossible. Other authors assume the score can take only two values (Athreya, Tam, and Young 2012) or that certain types of screening contracts are simply not possible (Sanchez 2017). Specifically, by assuming that behavioral and rational agents have the same beliefs (and thus preferences over available contracts), we entirely avoid adverse selection in the model. Thus, issues arising from possible screening contracts and potential non-existence of equilibria due to cream-skimming do not arise. Further, none of the existing credit-scoring papers models behavioral consumers, rather they typically focus on types that differ in patience or bankruptcy cost or riskiness.

The remainder of the paper is organized as follows. We describe our model in Section 2. The calibration is described in Section 3. Section 4 reports the main quantitative results on how type scores evolve over the life cycle and how the presence of over-optimists impacts credit markets. Section 5 analyzes how policies making default easier and taxing borrowing, and financial literacy education affect 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 are ignorant about that. 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.[8] 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 a history of consumer's income and expense shocks. While lenders know the fraction of the population that are over-optimists, λ, they cannot observe a consumer's type directly. Thus, lenders form beliefs over borrowers' types, which we term *type scores*, and update these beliefs each period based on a consumer's realized income shocks. The bond price schedule offered to a consumer reflects the expected default risk, and is thus influenced by the type score.

The model timing sees consumer productivity and expense shocks realized at the beginning of the period. Lenders update their type score. Then, consumers decide whether to file for bankruptcy, and if they do not file, how much to borrow or save.

[8]This paper focuses on unsecured debt. Given that unsecured debt is a small share of the overall financial market, the assumption that this has little effect on the risk-free rate of return is a reasonable approximation.

2.1 Households

Consumers maximize expected discounted life-time utility,

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

where β denotes the discount factor, the sequence of consumption levels $\{c_j\}_{j=1}^J$ is adjusted by household size n_j, δ_j is the indicator of filing for bankruptcy at age j, and χ is a utility cost of bankruptcy. $T \in \{R, B\}$ denotes a households type, rational ($T = R$) or behavioral ($T = B$). Behavioral consumers have over-optimistic expectations $\mathbb{E}^B$, which influence their consumption-savings choice (and consequently their debt holdings d) 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, they choose their consumption and debt (asset) level for the next period. They face a menu of debt prices (interest rates) $q(\cdot)$ that reflects their future default risk and is explicitly a function of how much they choose 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 the level of 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 level of debt they promise to repay next period (amount of defaultable bonds the household is selling to lenders). If the household is saving, the bond price is simply $q^s = \frac{1}{1+r^s}$. But if they borrow, the bond price q^b is a function the debt level d_{j+1}, the current realization z of the persistent income shock, household's age j, and their "type-score" s, which is the lenders' perception of the likelihood that the household is of 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:

$$y_j^T = \overline{e}_j z_j \eta_j^T, \tag{3}$$

where $\overline{e}_j$ is the life-cycle component, z_j is a persistent auto-regressive 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 risk 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") the types.[9]

Realists on the other hand have rational beliefs about their income risk. Their beliefs coincide with the true distribution of 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 bankruptcy in the US.[10] Filing for bankruptcy discharges the household's debt so a filer enters the following period

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

[10]A core element of consumer financial protection is the option to discharge debt. In the U.S., households can choose between Chapter 7 and Chapter 13 when filing for bankruptcy protection.[11] When a household's Chapter 7 bankruptcy filing is accepted, creditors lose any claims towards the bankrupt's future income in exchange for assets above a certain exemption level are seized. As a consequence of the 2015 Bankruptcy Abuse and Consumer Protection Act, Chapter 7 is now means-tested.[12] After declaring

with zero debt (unless hit with an expense shock that period). Individuals cannot file for bankruptcy in two consecutive periods, which captures the six-year exclusion from a repeat Chapter 7 bankruptcy in reality. Furthermore, filers must repay a fraction γ of their income when they declare bankruptcy. This captures the good faith effort required from borrowers to repay their debt as well as filing fees and legal fees. Bankruptcy filers also suffer a utility cost χ, which captures other costs (e.g, "stigma") associated with filing for bankruptcy. Because filers cannot save or borrow, the budget constraint in bankruptcy simply states that filers consume their income net of garnishment:

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

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 proportional transaction cost τ. They offer each borrower a personalized bond-price schedule, which is explicitly a function of the face value to be repaid next period, d'. Due to bankruptcy, repayment is (partially) state contingent. Intermediaries take into account expected losses from default when determining the bond price schedule $q(d', \cdot)$. Specifically, this price schedule depends explicitly 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.[13]

Specifically, type scores represent the probabilities that intermediaries attach to a household being rational. Although intermediaries cannot observe a household's type directly (i.e., realist or behavioral), they can observe the history of realizations of transitory income shocks η. Type score s summarizes the lenders' posterior belief about 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

Chapter 7 bankruptcy, consumers are exempt from re-filing for six years. Total filing cost comprise court fees and legal fees and range from roughly \$1,000 to \$1,700 (Sullivan, Warren, and Westbrook 2000). The court also demands a full list of creditors, outstanding debt, available assets, regular cost of living and the details on a debtor's income. Typical Chapter 7 bankruptcies rulings take four months till completion.

[13] 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.

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

2.3 Equilibrium

Under perfect competition and free entry in the financial market, lenders earn zero expected profits on each loan. Conditional on observable characteristics (persistent labor income z and age j) as well as 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 face value of the loan 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 simply the expected repayment next period discounted by the risk-free borrowing interest rate. We further introduce an interest rate cap $\overline{r}$, which can be thought of as a usury law. Loans that carry interest rates above this cap are banned by setting their bond price to zero. This yields the equilibrium loan price

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

Consumers take the equilibrium bond price schedule as given. 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 successive periods, we define the value of delinquency, $\tilde{V}$, for households not eligible for bankruptcy.[14] In delinquency, the same fraction of income is garnisheed as in bankruptcy and the debt is rolled over at a fixed interest rate r^r. All value functions depend on whether beliefs are rational or over-optimistic, $T \in \{R, B\}$:

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

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

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

An equilibrium is a set of value functions, optimal decision rules for 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 Theoretical Insights

Before proceeding to the quantitative analysis, we discuss two key qualitative model implications. First and foremost, the cross-subsidization in our model tends to go from

[14] Such delinquency addresses the possibility of an empty budget set for a consumer that is ineligible for bankruptcy but draws a large expense shock. The only debt held in this case stems from an expense shock.

the rational borrowers to the behavioral, not the other way around (as in Heidhues and Koszegi (2010), for example). This follows from the basic fact that the behavioral agents are more prone to be affected by adverse income shocks than their rational counterparts. And since these adverse shocks are one of the causes of bankruptcies, this implies that behavioral agents tend to default more often than rational agents taking on the same loans. Recall that the two types cannot be separated by a screening contract, which means that the equilibrium of our model features pooling and thus cross-subsidization. The cross-subsidization (which occurs within a type-score bin) goes from borrowers who are more likely to repay to those who are less likely to repay, as the pooled interest rate exceeds actuarially fair one for the former. In our setting, this implies cross-subsidization from rational to behavioral borrowers.

The second qualitative insight of our model is that transitory income shocks have long-lasting consequences by affecting the borrowers' type-scores and thus their future interest rate schedules. Thus, the very presence of behavioral agents has a non-trivial impact on rational borrowers, beyond the cost of cross-subsidization. Every instance of an adverse transitive income shock triggers a downgrade of a borrower's type-score, making borrowing more expensive. And this downgrade comes at the worst time, just when the individual needs to borrow in order to smooth the adverse income shock. Thus, the mechanism highlighted in Athreya, Tam, and Young (2009) for persistent shocks is present in our model even for transitory income shocks, due to the presence of multiple types and the type-score updating.

2.5 Welfare Measures

Since behavioral agents have distorted beliefs about the risk they face, their expected utility at birth does not correspond to the value that a planner would attach to their consumption stream (or the value that behavioral agents would assign if they were made aware of their true income process). Over-optimistic beliefs put excessive weight on positive outcomes and insufficient weight on adverse outcomes. Consequently, behavioral expectations do not correspond to the average outcomes of behavioral individuals. In order to evaluate the "true" welfare of behavioral agents being born into our economy, we introduce a welfare measure that is not distorted by the biased expectations.

We define paternalistic welfare of a newborn behavioral agent W^P as the utility that behavioral agents would expect if they used the correct rational expectations but still behaved ignorantly over their life:

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

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

3 Benchmark Calibration

Since much of the policy discussion surrounding behavioral consumers and the need for additional intervention is quite recent, we calibrate the benchmark model to recent U.S. data. Specifically, to smooth out some year-to-year fluctuations we use 5-year averages of the most recent available aggregate data (i.e., averages for the years 2013-2017). 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, several parameters are set externally, especially 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, modelled in 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).[15]

We follow Livshits, MacGee, and Tertilt (2007), in parameterizing the expense shocks to U.S. estimates of medical expenses, divorces, and unplanned parenthood.[16] The support of expense shocks, K, has three elements: $\kappa \in K = \{0, \kappa_1, \kappa_2\}$. The smaller shock

[15]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 3 decades.

[16]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

is 26.4% of average three year income. The large shock corresponds to 82.18% of 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.

Recall from Equation (3) that labor earnings involve a persistent and a transitory component. While there are many empirical estimates in the literature 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 no one, not even the consumers themselves, know that they are behavioral and that the true process is hence different.Instead, we use an overall process from the literature (specifically we use the process from Livshits, MacGee, and Tertilt (2010)) and then split the transitory component into two separate processes as explained further below.[17] 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: $\eta \in [\eta_1, \eta_2, \eta_3]$. Across the whole population (including behavioral and rational people), $\text{Prob}(\eta_1) = \text{Prob}(\eta_3) = 10\%$ of households receive a low or high transitory income shock each period. The support of the shock is set to match the variance $\sigma_\eta^2 = 0.05$ and have the mean of 1. Finally, each retiree receives a deterministic pension of 20% of average income in the economy, plus 35% of their last persistent income realization before retirement.

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 (to be defined below). We use data from the 2016 SCF to pin down these parameters.

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

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decades. Medical out-of-pocket spending remained essentially flat as a fraction of median household income. The number of births per 15-44 women remained flat too. The number of unwanted births slightly increased, at the same time divorces per 1.000 population declined a bit.

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

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

Recall that by assumption over-optimists differ from rational people only in the transitory income process. We assume now that they face the same shock magnitudes η_1, η_2, η_3 and differ only in the probabilities. We then define the degree of over-optimism as the ratio of the probability of a low transitory income realization of the two types of agents: Prob$^B(\eta_1)$/Prob$^R(\eta_1)$ and call this ratio ψ. To pin down ψ, we use a question in the SCF that asked consumers whether their income was higher, lower, or the same as usual. We find that respondents that we classify as behavioral (because of their poor performance in the financial literacy questions) are 1.36 times more likely to report an income that is "lower than usual." 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. The numbers are given in Table 1, see Appendix A for further details.

Note that our modelling assumptions means that behavioral people do not just have wrong beliefs, but that they truly face bad luck more often. In other words, we assume a negative correlation between being overly optimistic and expected income. Since we equate overoptimism with financial illiteracy here, 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.

3.2 Financial Market

We set the safe interest rate to $r^s = 1\%$ annually.[18] To pin down transaction cost in lending, we use the fact that average borrowing interest rates r^b are the sum of refinancing cost r^s, risk-premia ξ, and transaction costs τ (up to first order). The transaction costs of

[18]This is within the range of neutral real rates implied by the Laubach and Williams (2003) model.

lending is then simply given by $\tau = r^b - r^s - \xi$. We use data on charge-offs as a measure of the risk premium. As reported in Exler and Tertilt (2020), average charge-offs between 2013 and 2017 are $\xi = 3.3\%$.[19] The average real borrowing interest rate in 2013 - 2017 is $r^b = 10.6\%$. Exler and Tertilt (2020) construct this data from nominal interest rates on personal loans and credit cards[20] net of one-year ahead CPI inflation. 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 $\bar{r}$ — are chosen to target four data moments. The moments are calculated based on data described in detail in Exler and Tertilt (2020) and summarized in Table 2 below.

First, we target the fraction of consumers declaring Chapter 7 bankruptcy per year. For each year, this fraction is calculated by dividing total Chapter 7 bankruptcy filings, as reported by the American Bankruptcy Institute, by the total number of households as reported in the Census Bureaus 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 outstanding debts 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. The number from the 2016 SCF is 0.53.

We then choose β, γ, χ, and $\bar{r}$ to minimize the sum of squared relative residuals between model and data moments. While the model moments depend jointly on the pa-

[19] 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.

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

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)

rameters 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, utility cost of bankruptcy influence the frequency of default, recovery in bankruptcy change the risk-premium and thereby average borrowing interest rates, and the interest rate ceiling binds the coefficient of variation of borrowing interest rates. The model matches the data very well along all dimensions. We find an annual discount factor $\beta = 0.965$, the utility cost of bankruptcy are $\chi = 0.040$, lenders recover $\gamma = 39.5\%$ of loans that enter bankruptcy, and the interest rate ceiling is chosen to be $\overline{r} = 106\%$.[21]

4 Behavioral Borrowers: Financial Mistakes and Cross-Subsidization

We begin by examining how behavioral agents impact the pricing of credit as well as the overall level of filings when our economy is calibrated to match aggregate filings and unsecured debt. The key message from our experiment is that the partial pooling of behavioural and rational borrowers impacts the terms at which both types of agents access credit. This in turn influences borrowing and default decisions.

Our calibrated economy illustrates several interesting insights that arise in an environment with both behavioural and rational agents. While it is not surprising that behavioral borrowers *over-borrow*, what is less intuitive is that they also *file too late*

[21]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 more detailed discussion.

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%	-

for bankruptcy. These mistakes reflect both incorrect beliefs and the *cross-subsidization* of behavioural borrowers by rational borrowers. This cross-subsidization results from the (partial) pooling of types, which, conditional on the level of borrowing this cross-subsidization generally sees behavioral (rational) borrowers paying lower (higher) rates than would be actuarially fair. These two 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 behavioural 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 life.

4.1 Benchmark Outcomes

Our baseline calibration implies intuitive and 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, filings and the interest rate. Moreover, behavioral agents' incorrect expectations about future income result in their making systematic financial mistakes.

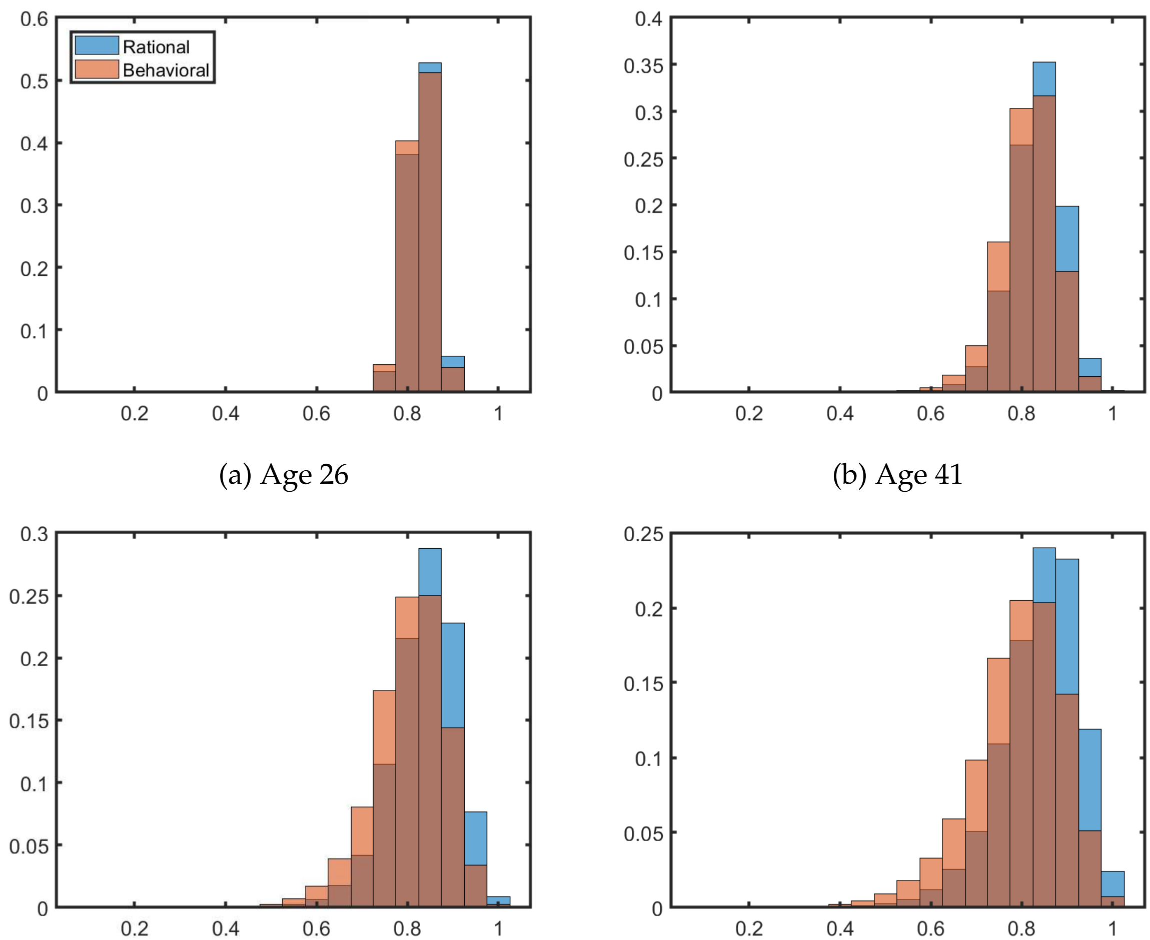
The differential pricing (on average) arises despite the inability of lenders to directly observe a borrower's type. Instead, they update their beliefs on a household type using type scores, which summarize the probability that a household is a realist. This implies that there is some pooling of types 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 score declining for realists and behaviorals. Conversely, type scores (weakly) monotonically increase for individuals who do not experience an adverse income shock. Since behavioural 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 keep a high score for their entire life, 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 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 distribution 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.

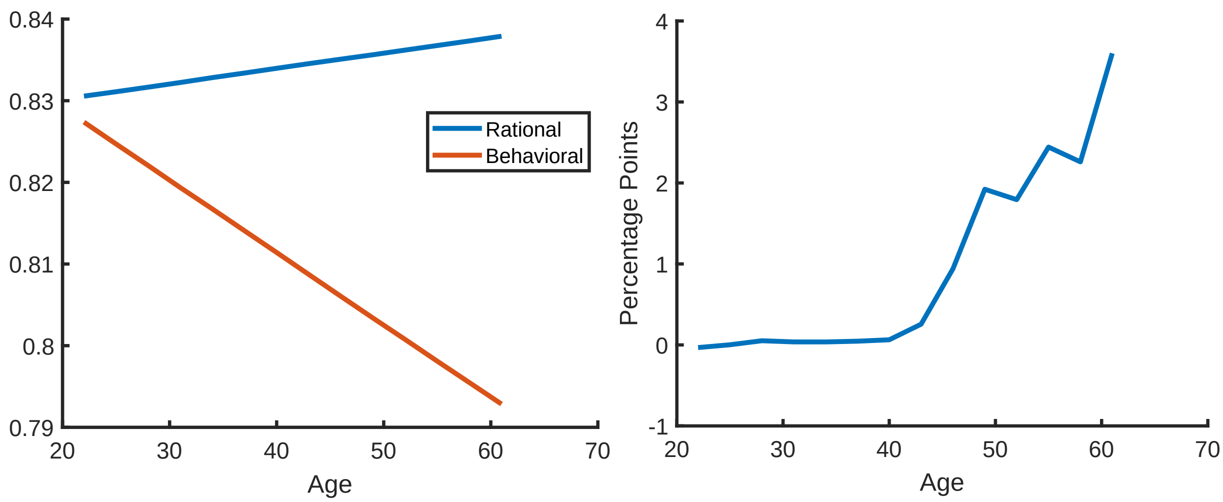
The divergence in type scores over the life cycle (see Figure 2a) reduces the pooling of borrowers. Consequently, average borrowing interest rates for behavioural borrowers drift away from those of rational borrowers with age (see Figure 2b). In addition to the effect of more accurate type scores which reduces cross-subsidization, the rising gap in average interest rates reflects 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.



(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

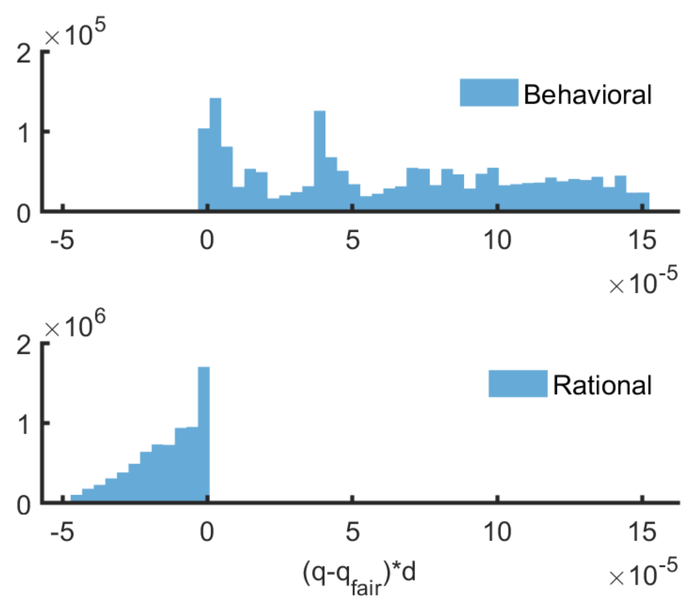


Figure 3: Distribution of Cross-Subsidization

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 equilibrium interest rate schedules (i.e., lenders remain unaware of the agents' types) and agents' past choices (before being informed of their true income risk).

While overborrowing by over-optimists is not surprising, filing too late is less intuitive, especially given that they file much more often than rationals (see Table 3). We define "filing too late" as a behavioral households who chose 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 they 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 defaulting 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 behavioural 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

Borrowing and default decisions of behavioral consumers are shaped their over-optimism, by the fact that they are truly more risky than rationals, and by the partial pooling of types. To decompose the contribution of these factors, we calculate several counterfactual economies, changing one dimension at the time. Specifically, Table 4 shows three counterfactual economies populated solely by one type of household, with and without

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

Income Process	Better Risk	Worse Risk	Worse Risk	Worse Risk
Beliefs	Realistic	Realistic	Overoptimistic	Overoptimistic
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 process). (2) Beliefs can either be *realistic* or *overoptimistic*. (3) Agents can either populate an economy alone – *not pooled* – and receive actuarially fair prices or be *pooled* with 83% realists.

over-optimistic beliefs, and with different income processes and compares them in the last column to the behavioral consumers in our calibrated economy (in which rational and behavioral agents are pooled).

These experiments show that the direct effect of the difference in transitory income risk between realists and behavioural households is 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 behavioural agents. Since these economies are populated by one type, not only are expectations correct, 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 overoptimistic 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).[22] The observed impact of filings appears to be more modest, as filings are roughly 10 percent 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 overoptimistic 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 a rational agent would choose to default. This results in *lower* average interest rates (compare column 3 and 2 in Table 4). This is a consequence of two effects. First, there are 15% more borrowers when beliefs are overoptimistic (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 overoptimistic. This commitment-to-repay effect decreases interest rates.

The final column of Table 4 reports the outcomes for behavioural 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 on average debt of cross-subsidization 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 average borrowing rates of over-optimistic households: their average interest rates is *higher* when pooled with rational households (11.12% versus 9.81%). This results arises due to subtle impacts of cross-subsidization on the probability of default and loss given 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

[22]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 given a history of behavioral debt choices and at fixed prices.

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 lead to 4% more filings per borrower. Cross-subsidized interest rates thus results in both a higher probability of default per borrower and higher loss given default as filers are more indebted. On average, the interest rate for behavioral borrowers *increases* by 131 basis points despite them receiving subsidized loan contracts.

4.3 Fraction of Behavioral Agents

While behavioral borrowers are central to the current policy debate and it is hard to argue that all agents always employ rational expectations when making borrowing decisions, there is no consensus in the literature about the precise fraction of agents that are behavioral. According to the definition in our calibration strategy, 17% of SCF respondents are financially illiterate and are termed behavioral in our model. However, one might employ different definitions to arrive at different fractions of behavioral agents. This section documents the effect of different compositions of behavioral and rational agents in our framework. Table 5 documents aggregate and individual outcomes when varying the fraction of behavioral agents in the economy. This analysis compares different steady states ceteris paribus, i.e. without adjusting any of the other parameters of the model.

Reading Table 5 from left to right presents the effects of pooling on rational agents: relative to an economy where rational agents are by themselves ($\lambda = 0$), introducing more and more behavioral agents means that rational borrowers face more and more pooling. Since, behavioral agents are worse risks, more pooling implies higher *quoted interest rate schedules*. In equilibrium, higher interest rate schedules lead to lower debt holdings. Consequently, the debt-to-income ratio of rational borrowers falls monotonically in the fraction of behavioral agents. This leads to (monotonically) lower bankruptcy filings of rational borrowers. Thus, also average *realized interest rates* of rational borrowers decline monotonically in the fraction of behavioral agents.

Reading Table 5 from right to left, one can analyze the effects of increased pooling from a behavioral agent's standpoint. The mechanisms are the exact mirror image of

Table 5: Varying the Fraction of Behavioral Agents

	Fraction of behavioral borrowers λ						
	0	0.1	0.17	0.3	0.5	0.75	1
Debt-to-income							
Rational	6.38%	6.37%	6.37%	6.36%	6.35%	6.33%	
Behavioral		8.22%	8.22%	8.21%	8.21%	8.21%	8.19%
Average		6.55%	6.67%	6.90%	7.27%	7.73%	
Bankruptcy filings							
Rational	0.44%	0.44%	0.44%	0.43%	0.43%	0.43%	
Behavioral		0.53%	0.53%	0.52%	0.52%	0.51%	0.51%
Average		0.45%	0.45%	0.46%	0.47%	0.49%	
Average interest rates							
Rational	10.59%	10.51%	10.40%	10.17%	9.92%	9.61%	
Behavioral		11.36%	11.12%	10.86%	10.52%	10.06%	9.81%
Average		10.62%	10.55%	10.41%	10.25%	9.96%	

those affecting rational agents. Relative to an economy without pooling ($\lambda = 1$), introducing more and more rational agents increases pooling for behavioral borrowers. Thus, interest rate schedules quoted to behavioral borrowers decline leading to higher debt-to-income ratios, higher bankruptcy filings, and consequently higher average interest rates for behavioral agents.

Average outcomes are driven by changes in individual behavior and by a composition effect. Even though both types of agents hold less debt and default less in an economy with many behavioral agents, the composition effect dominates: the average debt-to-income ratio and average bankruptcies increase in λ simply 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. They decline in the fraction of behavioral agents λ. Even though behavioral agents pay higher interest rates for any given fraction λ, both agents individually pay lower average interest rates the higher the fraction λ. These individual interest rate effects dominate the composition effect.

5 Consumer Protection Policies

Proponents of credit market regulation often argue it can improve the outcomes of consumers who do not behave fully rationally or have limited financial literacy.[23] 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 easier. Since, conditional on type score, over-optimists are indistinguishable from realists, these policies apply to everyone.[24] 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 policy experiments are summarized in Table 6.

[23] 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 "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."

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

5.1 Higher Borrowing Costs

A central argument for regulating consumer credit is to preempt overborrowing. This motivates a number of policies aimed at reducing the incentives to (over)borrow, ranging from limiting 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 consumer financial regulations is an increase in the costs of lending. Higher cost of lending translate into higher interest rates which – independent of the specificities of the law – hamper borrowing. Consequently, if individuals make financial mistakes such as overborrowing, a higher cost of lending might be beneficial if it discourages "mistaken" borrowing. On the other hand, there is a clear deadweight cost attached to higher cost of lending. Moreover, a higher borrowing cost affect everyone, including rational people that use credit correctly.

Our borrowing cost experiment increases the risk-free lending rate by one percentage point, from 7.3% in the benchmark to 8.3%. As can be seen from the second column in Table 6, higher borrowing costs result in lower borrowing and lower bankruptcy filings. If a policy makers objective were to reduce debt and bankruptcies, then this policy would be successful.[25]

However, we find that both types of agents dislike higher borrowing costs. It is not surprising that rational consumers, who were not making financial mistakes, are made worse off when credit becomes more expensive. What is surprising is that the welfare losses are larger for over-optimists than rationals. The reason is that even though *borrowing* declines, our measure of *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 are large enough to reduce behavioral agents' welfare more than that of rational agents. This policy, however, does reduce mistakes in the timing of filings. While 0.29% of behavioral people filed too late in the benchmark, this declines to only 0.11%.[26] However, this benefit is not enough to outweigh its substantial direct costs.

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

[26]This reduction in filing too late does not lead to higher filing rates. Rather, behavioral agents file earlier, since in the presence of higher borrowing cost roll-over becomes more expensive. Consequently, even if behavioral borrowers over-estimate their ability to repay they are more prone to default right away due to higher borrowing cost.

Table 6: Policy Experiments

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

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

5.2 Lower Cost of Default

To target the mistake of 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 the benchmark level of 39.5% to 30%. This reduction in the cost of default substantially increases the default rate of both types of agents. Furthermore, lower default costs tightens the endogenous borrowing constraints debt in equilibrium since higher default rates and loss given default lead lenders to increase their interest rate schedules. As a result, average borrowing interest rates jump to 13.37%. Due to higher borrowing costs, households nearly cut their debt-to-income ratio in half.

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

Unlike a policy that targets a higher cost of borrowing, in our model lowering the cost of default increases welfare (see Table 6). However, this positive welfare effect is present for both types of consumers, so that the gains from limiting financial mistakes by over=optimists are meagre. Rather, these gains are reflect a well documented feature of this class of consumer bankruptcy models. A more lenient bankruptcy system can be better as it increases insurance against adverse shocks (see Livshits, MacGee, and Tertilt (2007) and also the recent survey by Exler and Tertilt (2020)).

5.3 Financial Literacy Education

Neither of the policies considered above reduces both types of financial mistakes. Thus, we conduct a policy experiment where we remove the over-optimism of behavioral agents about their future transitory income risk, the underlying reason they make financial mistakes. Under "financial literacy education," we educate behavioral agents about their true risks to eliminate overborrowing and filing too late completely. In this counterfactual, all agents are perfectly informed about their true income process. We assume that behavioral agents become perfectly identified to themselves *and* to lenders. As before, we focus on a paternalistic measure of welfare.[27]

[27]This policy directly reduces perceived welfare of behavioral agents by mechanically lowering their expectations. Behavioral agents are overoptimistic and informing them about their actual risk directly

This policy is a useful counterfactual to understand the effect of directly addressing wrong beliefs as the reasons of financial mistakes. However, it worth emphasizing that such a policy could not be implemented perfectly in practice. In our environment, neither consumers nor lenders know who is behavioral. In such a world introducing an omniscient government that knows each consumer's type is a stark assumption. As we abstract from issues of implementation, our findings can be interpreted as the upper bound for policies that at improve the awareness of behavioral agents.

As be seen from column (4) of Table 6, perfectly informing behavioral agents about their income process has two opposing effects on behavioral agents. First, as they now have correct expectations about their income, they no longer make financial mistakes.[28] As a consequence of learning their true income process, behavioral agents realize that they are poorer than expected and accordingly 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 find themselves less often in a situation of high outstanding debt and bad income realizations. Consequently, they file for bankruptcy less often. Lower amounts of debt and fewer defaults lead to lower *average realized* interest rates in equilibrium for behavioral people.

At a first glance, financial literacy education appears to be a successful policy: imposing correct expectations reduces 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 behavioural borrowers are no longer (partially) pooled with rationals. In the benchmark, the partial pooling of behavioral borrowers with rationals result in their being cross-subsidized through lower interest rate schedules.[29] 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 the cross-subsidization which lowers the interest rate *schedules* they are quoted. Rational

worsens their perception (i.e. ignorance is bliss).

[28]For simplicity, we continue to refer to these (now) informed poorer agents as "behavioral" even though they are technically not behavioral anymore.

[29]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.

agents react by borrowing slightly more which leads to slightly higher *average realized* interest rates in equilibrium. Equipped with better credit terms, realists marginally gain in welfare terms, 0.02% in 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 income (DTI).[30] 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 taking their income into account.[31] DTI limits are often mentioned in the context of macroprudential regulation.

To implement DTI limits in the model, we use current persistent income $\overline{e} \times z$ 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: $q(\cdot)d'/(\overline{e}z)$.[32]

We report the effects of a relatively loose debt to income limit of 100% in column (5) of Table 6. Despite being a relatively lax limit, limiting the debt to income ratio to 100% prohibits very large loans, which results in rational and behavioral agents outstanding debt declining by about 1.6 to 2 percentage points. Smaller outstanding debts are easier to repay and lead to fewer bankruptcies in equilibrium. Fewer bankruptcies lead to lower risk premia and 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, total welfare effects are negative. Agents lose 0.31% in consumption

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

[31] 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.

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

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 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

The previous section documented that untargeted borrowing limits for all agents can reduce financial mistakes but also have negative welfare effects. Hence, it seems promising to focus policy interventions specifically on consumers that make mistakes. However, policy-makers cannot identify these agents perfectly in reality. Credit scores might serve as a proxy. A low score may indicate that borrowers regularly make financial mistakes. While we have no theory of credit scoring, our framework generates type scores endogenously. These type scores reflect lenders' beliefs about a borrower's behavioralness and thus indicate a consumer's proneness to financial mistakes.

In this section, we explore the effect of targeting debt-to-income limits to agents with a low type score (and a high probability of being behavioral).[33] In contrast to Section 5.4, we analyze a debt to income limit that applies only to consumers below a certain type score threshold. That allows agents that are very likely rational and have high type scores to borrow without without being restricted.

We find that targeted debt to income limits – similar to the untargeted limit in Section 5.4 – tends to reduce debt, defaults, and interest rates which is typically a prime objectives of regulating the credit market. Also similar to untargeted borrowing limits, targeted policies lower welfare due to restricted access to credit for some.

To see what fraction of the population is affected for a given type score threshold, Figure 4 plots the CDF of the type score distribution. It shows policies that apply to scores below 0.6 affect almost no one (<1%). Approx. 6% of the population have a type score of 0.7 or smaller and 40% have a type score of 0.8 or smaller. Only approx. 5% of the population have a type score strictly above 0.9. For each score, the figure also shows the decomposition between rational and behavioral consumers at or below this

[33]Policies explicitly targeted at households above or below a threshold are quite common in reality. Mitman (2016) for example analyze HARP introduced in 2009 which essentially gave borrowers with loan-to-value ratios between 80 and 125% an interest rate subsidy and finds large welfare effects.

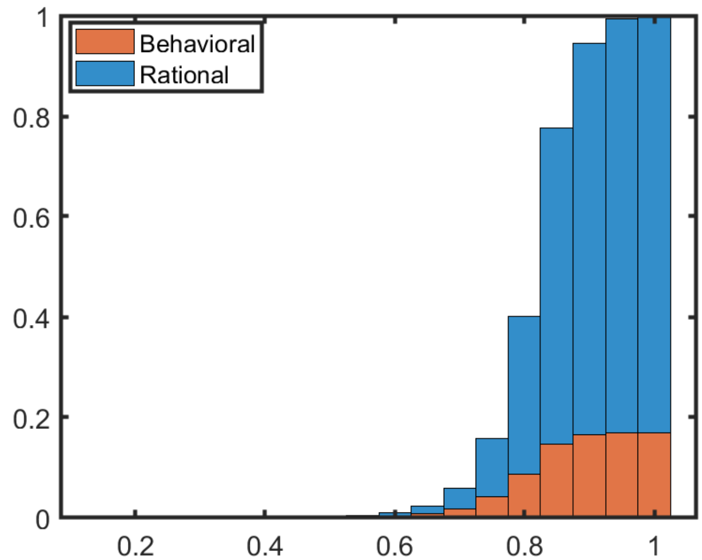
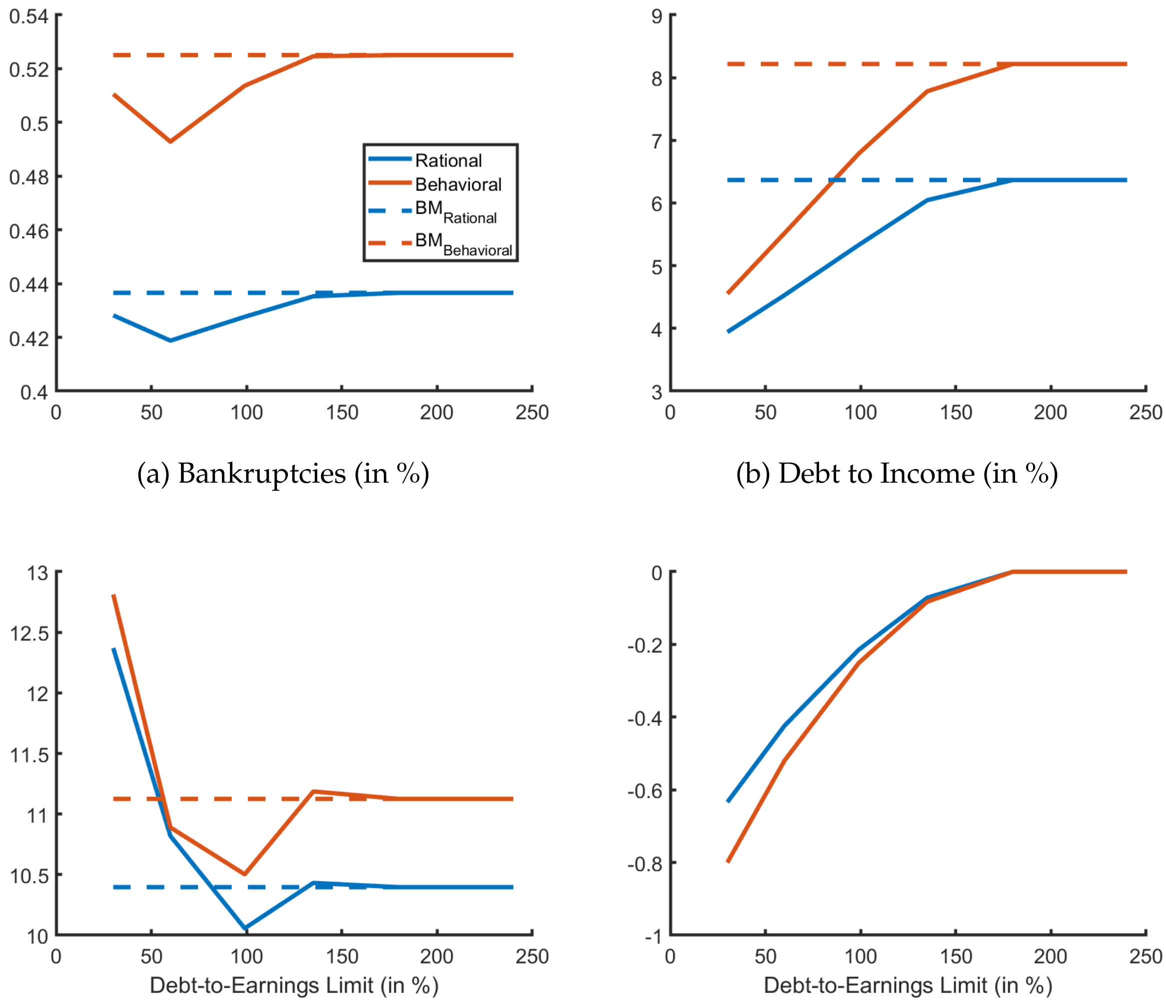


Figure 4: CDF of Type Scores, split by type. See Table 10 in Appendix D for underlying numbers.

score. For the whole population (at or below a type score of 1), there are 17% behavioral agents. Since behavioral agents tend to have lower type scores on average, this measure increases for lower type scores: at or below 0.75, there are 26% behavioral agents, at or below 0.4 behavioral agents are in the majority. When targeting regulation to behavioral agents, policy makers thus face a trade-off between precision and coverage. On the one hand, lower thresholds target behavioral agents more precisely in that they affect fewer rational agents inadvertently. However, many behavioral agents are not covered by low thresholds. On the other hand, higher thresholds have higher coverage. However, besides affecting more behavioral agents they also cover more rational agents, too.

We explore two dimensions of type score dependent DTI limits: the effect of varying the debt-to-income limit itself and the effect of varying the type score threshold below which borrowers are subject to the policy. Appendix C gives further details on the exact definition of the policy in the model.

First, we focus on fixing the type score threshold to 0.8 and varying the debt-to-income limit. Agents with a lower type scores are subject to the debt-to-income limit. In equilibrium, the policies applies to about 40% of all people, see Figure 4. One might think that a type score threshold of 0.8 captures mostly behavioral people. However, recall that the calibration determines only 17% of agents to be behavioral. Since unlucky



(a) Bankruptcies (in %)

(b) Debt to Income (in %)

(c) Interest Rates (in %)

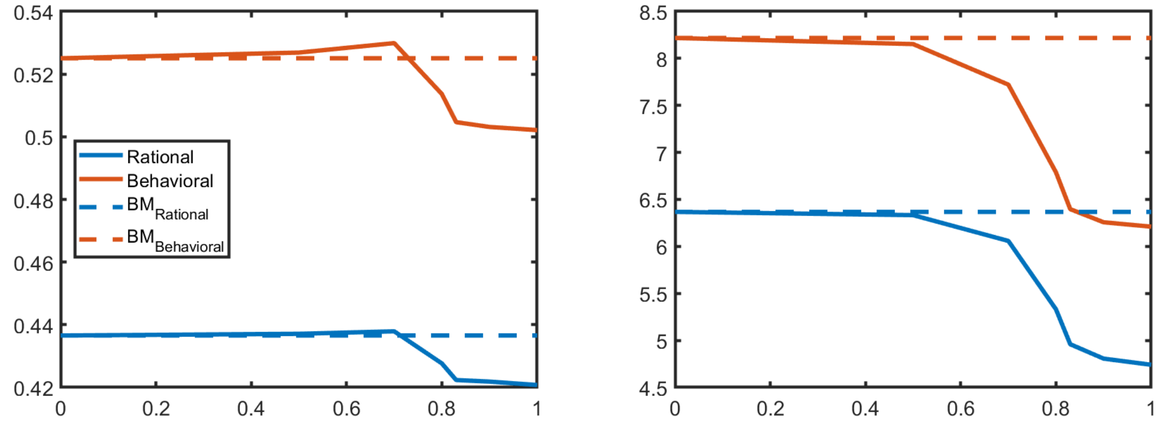
(d) Welfare (in % CEV)

Figure 5: Debt to Income Limits at Type Score 0.8

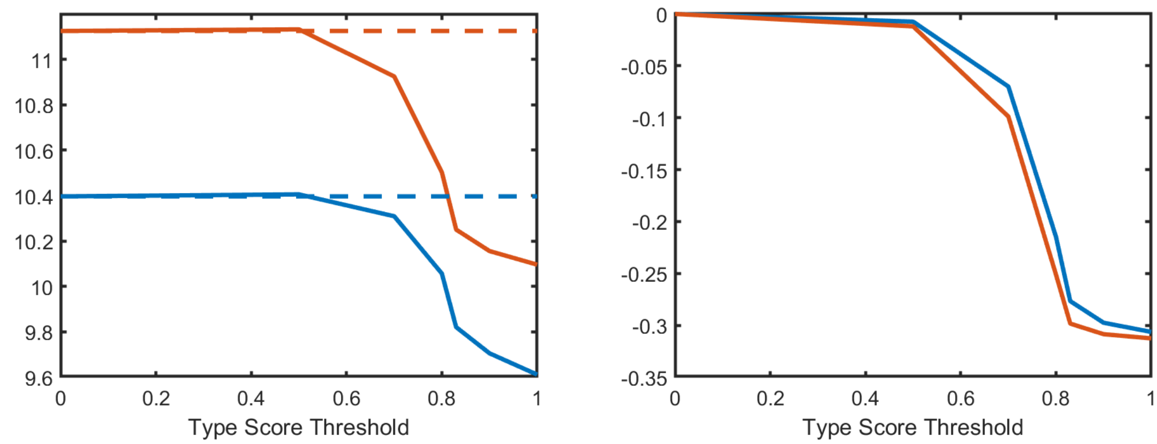
rational agents also face deteriorated type scores, learning is far from perfect. Figure 4 shows that less than a third of people with a score of 80 or lower are actually behavioral.

The effects on bankruptcies, debt, interest rates and welfare are displayed in Figure 5 – for a debt-to-income limit ranging from 30% to 240% of annual income. Not surprisingly, the lower the debt-to-income limit, the lower is average debt (panel b). Note that once the limit reaches about 170%, it stops to be binding and all measures revert to benchmark values. This is a large number given that the average debt-to-income ratio is only 6.7%. Do more binding debt-to-income limits also lead to lower filing rates? Initially yes, as panel (a) shows. This is likely the effect most policy-makers have in mind when implementing such limits – preventing people from "borrowing too much" and accordingly "filing too much." However, with even lower limits filings increase again. The reason is that a low limit on debt also prevents people from borrowing who are good credit risks but experience temporary bad shocks (e.g. an expense shock). If the shock is particularly large, some people have no choice but to file for bankruptcy. In the absence of regulation, they could have borrowed (and repaid) without declaring bankruptcy. This effect constrains more people the lower the debt-to-income limit is. Therefore, bankruptcy filing rates are u-shaped in the debt-to-income limit. For the same reasons, interest rates are u-shaped in the debt-to-income limit, too. The tighter the limit, the more low-risk consumers stop borrowing, while people who are bad credit risks, but desperate, will continue to borrow. This selection leads to increasing average interest rates far above the benchmark level. Looking at welfare, stricter debt-to-income limits are not a good policy, even in the range where filings decrease average welfare measured in consumption equivalence terms declines. The reason is not only that rational agents become constrained. In fact, behavioral agents' welfare declines even more. Thus, even though the policy successfully reduces debt and potentially bankruptcy filings, it is not successful in increasing welfare.

These negative welfare effects might occur because the type score threshold of 0.8 is too high. Thus, we fix the debt-to-income limit at 100%, where interest rates are reduced the most. We then vary the type score threshold, see Figure 6 for results. The score threshold varies from 0 to 1, 0 representing a regulation where everyone clears the threshold and is unconstrained and 1 representing a regulation where all agents are subject to the debt-to-income limit. The latter corresponds to column (5) in Table 6. Clearly, for low thresholds the policy hardly applies to anyone (see Figure 4), explaining the almost flat lines until about 50. Once the debt limit becomes binding for a sizeable fraction



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



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

Figure 6: Debt-to-Income Limit of 100% with Changing Type Score Thresholds

of people and increasingly those that may in fact not be behavioral, then average debt starts to fall and similarly bankruptcies go down as well. 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 groups.

Making regulations and restrictions dependent on borrowers' type scores is intuitively attractive, as it disproportionately targets behavioral borrowers. But this feature of policy is likely to have a non-trivial adverse effect. Such policy will tend to bind and restrict an individual's borrowing at the worst possible time, exactly when the individual has the largest need to borrow. Adverse transitory income shocks necessitate borrowing on the one hand, but they also lower a borrower's type score on the other hand. If the latter triggers an additional restriction on borrowing, the 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. To that end, we introduce over-optimistic borrowers into an economy with unsecured debt and equilibrium default. Households are subject to idiosyncratic earnings and expense shocks. Rational households hold correct beliefs about the future while over-optimistic households think of themselves as realists but actually face systematically higher expense risk. Lenders price credit endogenously but cannot directly distinguish household types. By observing income and expense shock realizations they form type scores (i.e. beliefs about the probability of a household being rational). In equilibrium, spill-overs arise between rational and over-optimistic borrowers with the same type score. Because over-optimists default particularly often, cross-subsidization goes from rational to behavioral consumers.

When more over-optimists populate our economy, the average interest rate goes up. Both types borrow less and default less on an individual level. However, aggregate debt and aggregate bankruptcies increase due to a composition effect: when increasing the fraction of over-optimists, the economy is composed of more risky households that borrow and default more. Due to overestimating their ability to repay, over-optimists borrow too much and default too late compared with the paternalistic benchmark.

To address these inefficiencies, we explore three potential policy reforms. First, we reduce default cost, inducing over-optimistic people to default earlier. While this increases over-optimistic welfare, rational people suffer from tighter borrowing limits they face. Second, we investigate financial literacy education where we inform consumers and lenders about the true types. Over-optimists are be made worse off by facing their true, higher than expected, exposure to risk. Furthermore, they do not benefit from cross-subsidization anymore. Rational people on the other hand benefit from the policy because they are no longer pooled with the high-risk over-optimists. Linking to the current policy debate, some of the voiced concern about naive consumers could be driven by self-interested (rational) policy-makers not wanting to cross-subsidize behavioral borrowers. Third, we explore the implications of making borrowing more costly in order to reduce over-borrowing. However, both groups are made worse off by facing significantly higher interest rates.

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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 concerning the financial literacy of households. Among others, three questions testing basic financial knowledge of the respondent were included (X7558 to X7560). These questions were on the topics of risk diversification, interest rate compounding, and inflation. We counted for each respondent how many of the three questions were answered correctly to get a measure of financial literacy. Table 7 shows that only 50% of respondents get all questions right, while 32% answer exactly 2 correctly, 13% get only one right and 4% answer all questions incorrectly. The table also shows that the number of questions answered correctly is highly correlated with education and income. Comparing those that get at most one question right with those that get all 3 right, their income is less than a third, and the fraction with a college degree is also substantially lower.

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 received 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 percent experienced unusually low income, compared to only 14 percent 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

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

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

To define the DSR, we relate interest rate payments to income: $(1 - q(\cdot))d'/(\bar{e}z)$. We define the DSR solely 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, and since the effects of incorporating principal payments is roughly equivalent to a tighter cap on our interest based DSR.

B.1 Untargeted DSR Limits

Table 9 replicates Table 6 but includes 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 type 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 ratios decrease 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

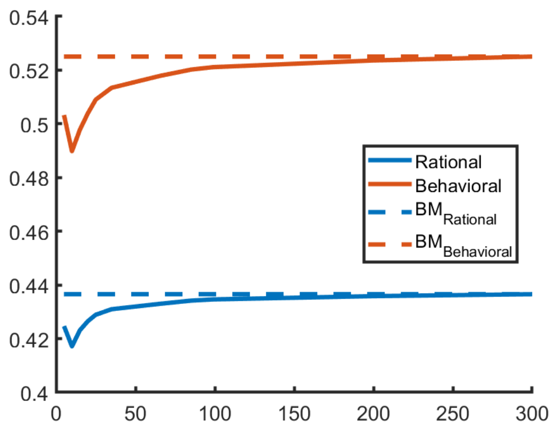
In line with Section 6, we also investigate DSR limits when they only applies to consumers with a type score below a certain threshold. The logic is the same as before: consumers with a low score are more likely to be behavioral and make financial mistakes. They might need to be protected from "borrowing 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). Lose limits (roughly 300% and higher) are non-binding and hence debt, filings, interest rates and welfare are all at benchmark levels. As the DSR limits get tighter, filings and debt decline and interest rates fall. However, filings and interest rates are non-monotonic in the limit. For even tighter limits, filings rise again and accordingly interest rates increase as well. The reason is similar to the one discussed above: at some point tight limits also affect good credit risks preventing them from borrowing when they need it and thus driving them into bankruptcy.

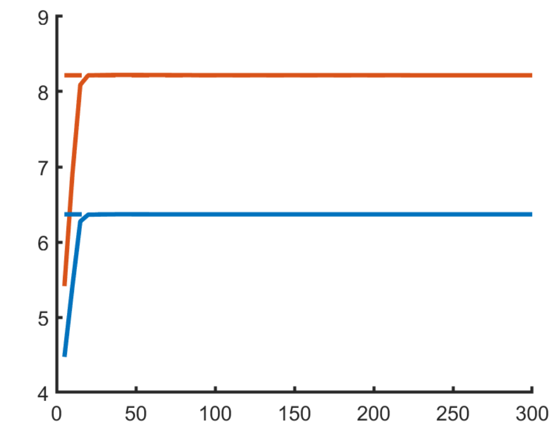
Table 9: Policy Experiments with DSR

	(1)	(2)	(3)	(4)	(5)	(6)
	Bench-mark	Borrow Cost $\nearrow$	Default Cost $\searrow$	Financial Literacy	Debt-to-income	Debt Service Ratio
Parameter		$\tau = 7.3\%$	$\gamma = 30\%$		$\leq 100\%$	$\leq 45\%$
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%

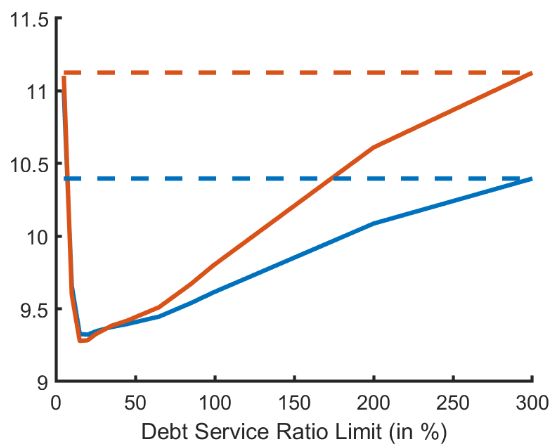
Note: Welfare is expressed as consumption equivalence variation relative to Benchmark (BM).



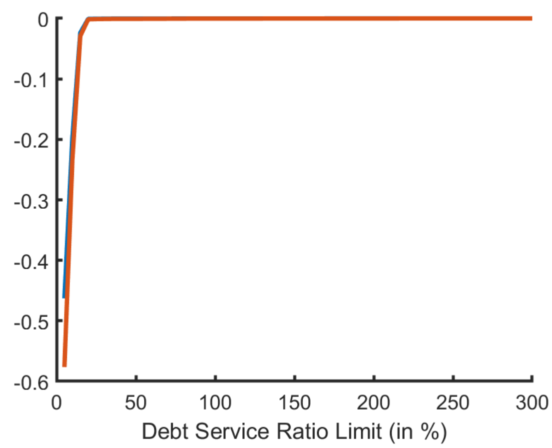
(a) Bankruptcies (in %)



(b) Debt to Income (in %)



(c) Interest Rates (in %)



(d) Welfare (in % CEV)

Figure 7: Debt Service Ratio Limits at Type Score 0.8

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 bind most on high interest rate loans, mechanically driving down average interest rates.

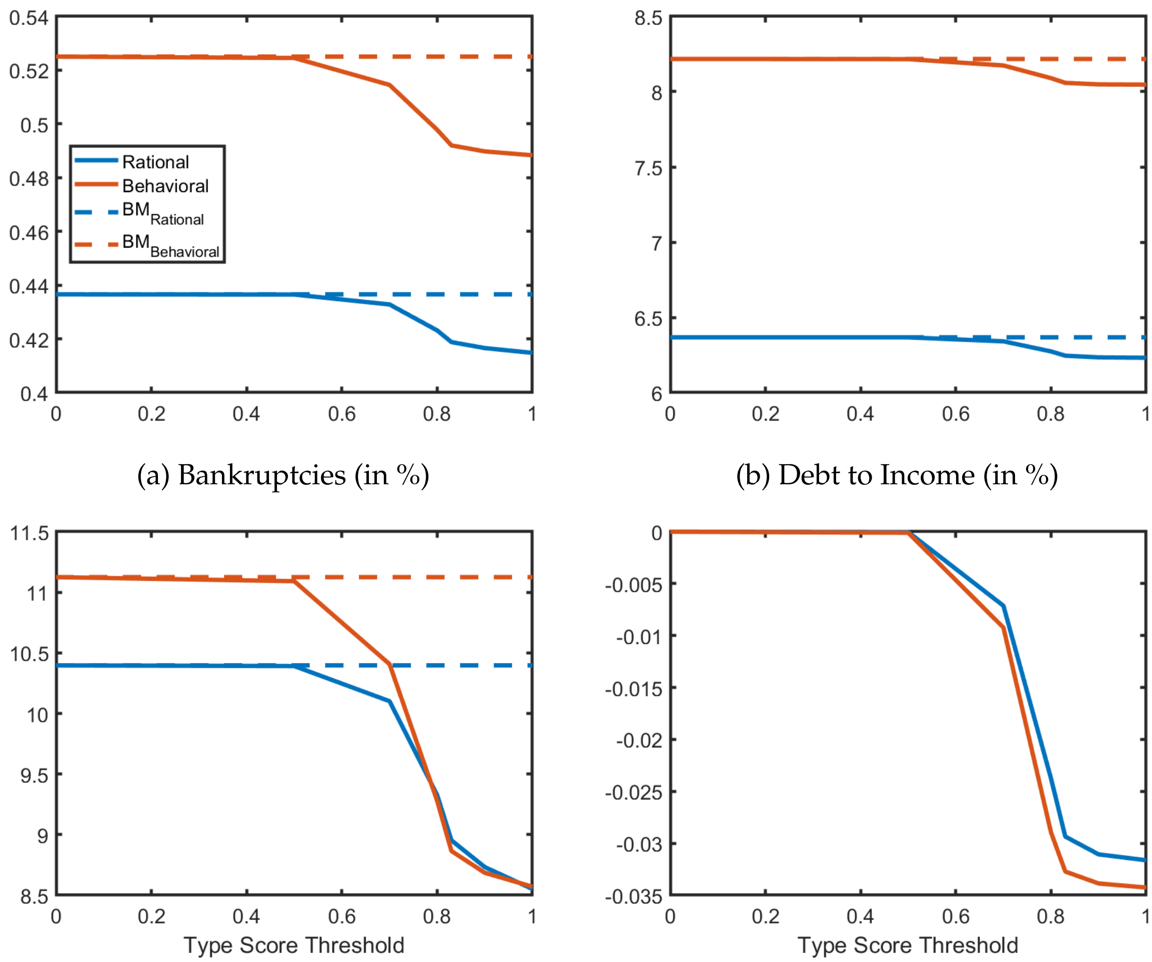
To investigate the effects of changing the type score threshold, we fix the DSR limit to 45% (which was shown to effectively reduce interest rates and bankruptcies) and vary the type score threshold from 0 – no one is subject to the DSR limit – to 1 – everyone is subject to the DSR limit. The latter 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 rate, 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 type 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 exact 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



(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

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 borrow in that period. Recall that in our notation d' is the promised repayment including the interest rate (rather 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 predicted future income, rather than 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 Equilibrium

	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%