Consumer Credit with Over-Optimistic Borrowers[*]

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July 17, 2024

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

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

JEL Classifications: E21, E49, G18, K35

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

1 Introduction

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

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

The coexistence of over-optimistic and rational consumers allows us to study how the endogenous pricing of credit risk leads to spillovers from the borrowing and default decisions of different types. We show that over-optimists, who make mistakes in their borrowing and default decisions, are cross-subsidized by rational borrowers. As we show theoretically, these mistakes can create scope for welfare-improving regulation, which leads us to analyze several policies that target these mistakes. We find that even when these policies reduce mistakes and target borrowers that are likely over-optimistic, they often fail to improve welfare.

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

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

We explore over-optimism about future income, rather than other specifications of behavioral consumers, for two reasons. First, this assumption gives rise to a tractable model of type scoring and partial pooling of behavioral and non-behavioral consumers.[3] Second, substantial empirical work has documented that some consumers are over-optimistic about their future income (Arabsheibani et al. 2000; Dawson and Henley 2012; Balasuriya and Vasileva 2014; Balleer et al. 2021; Mueller, Spinnewijn, and Topa 2021; Mueller and Spinnewijn 2023).[4] Moreover, they generally underestimate the probability of experiencing negative events (Weinstein 1980; Puri and Robinson 2007). Motivated by these findings, we assume that some consumers are over-optimistic and place too low probabilities on negative transitory income shocks.[5]

Since we assume over-optimists believe they face the same risks as rational consumers, they differ from realists in being more prone to bad shocks *and* being unaware of the worse risks they face. Although conceptually these are distinct features (and we decompose the contributions of each channel), in practice they often come hand in hand. Controlling for education, we document that respondents in the Survey of Consumer Finances (SCF) with low financial literacy scores report being surprised by low-income realizations more often (and have lower income on average) than individuals with high financial literacy. Not surprisingly, we find that low literacy scores are more common amongst the non-college educated than amongst those with at least a Bachelor's degree. Relatedly, Balleer et al. (2021) document that US households are over-optimistic about their labor market prospects and that the extent of over-optimism is greater for the less educated. This pattern of being more exposed to shocks co-existing with over-optimism has also been documented for the self-employed. Despite facing more income risk than wage

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

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

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

earners, the self-employed have been found to be more over-optimistic than the average population (Åstebro 2003; Arabsheibani et al. 2000).

Our quantitative model incorporates over-optimistic households in an incomplete market economy with bankruptcy populated by finitely-lived heterogeneous agents subject to idiosyncratic earning shocks and stochastic expenditures (i.e., "expense shocks"). Households choose how much to borrow or save and whether to file for bankruptcy. There are four types of households: college and non-college educated households are either realists who hold correct beliefs about the uncertainty they face or over-optimists who believe they are realists (and, behave as realists) but face systematically worse risk. If households do not default, they can borrow or save in a one-period bond that is priced in a competitive debt market.

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

To illustrate how default shapes the pattern of cross-subsidization and the potential role of regulation to limit borrowing, we analyze a two-period environment with over-optimistic and rational consumers. We show that the pooling of borrowers with heterogeneous default probabilities results in the riskier type being cross-subsidized by the less risky. In the two-period model, over-optimists make two offsetting mistakes: they over-estimate the probability of repaying debt, but underestimate the costs of default. When the cost of default exceeds the cost of repaying, then consumer protection regulation which limits access to risky debt (i.e., debt which sees default in equilibrium) can sometimes be welfare-improving.

A corollary of this is that conditioning the borrowing restrictions on a type-score can further improve welfare by better targeting the policy.

To quantitatively assess the effects of these policies, we calibrate our model to the U.S. economy. Our calibration results in a fraction of over-optimists in the non-college population of 31%, roughly twice that of the college population. As a result, lenders assign a higher probability that a non-college consumer is an over-optimist. Non-college consumers also have a flatter life-cycle earnings profile than the college educated.

Over-optimistic consumers have higher levels of debt and default more often than rational consumers. Our decomposition shows that the higher debt levels are primarily driven by the incorrect beliefs of behavioral borrowers, while the higher default rate is largely due to their worse income risk. These incorrect beliefs lead to mistakes by over-optimists who over-borrow and file too late compared to what an informed version of themselves would do. In our calibrated economy, if suddenly made aware, behavioral consumers would borrow about 8% less and bankruptcy filings would increase by nearly 9%. This arises because over-optimistic beliefs about future income encourage borrowers to postpone defaulting as they expect to repay their debt. Ex post, however, over-optimists are systematically surprised by lower income realizations, which sometimes leaves them unable to repay.

These mistakes seemingly support the case for regulations to protect behavioral consumers. However, this conclusion overlooks a mechanism working in favor of these consumers. In equilibrium, spillovers between rational and over-optimistic borrowers arise from their partial pooling. As we show analytically in our two-period example, equilibrium default combined with over-optimists being the higher risk type due to a greater likelihood of negative income shocks result in rational borrowers cross-subsidizing the behavioral borrowers they are pooled with. Regulation that reduces cross-subsidization could thus harm behavioral consumers.

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

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

Reducing default costs increases welfare for behavioral consumers and reduces the frequency of non-college educated late filings. However, since rational consumers benefit equally, these gains are not driven by fewer mistakes by over-optimists. Instead, in our calibrated model, overall default costs exceed their welfare maximizing level. We find that a tax on borrowing lowers the welfare of both types of consumers and has mixed effects on over-borrowing and filing of different education groups. Similarly, we find that introducing a cap on debt-to-income ratio results in lower welfare for both types of consumers. However, a debt-to-income cap succeeds in almost eliminating late filings by over-optimists.

Given the limited success of the above policies, we explore whether more-targeted policies can improve welfare. Since directly targeting behavioral people is impossible in our model, we analyze debt-to-income limits targeted at borrowers with a low type score (and a high probability of being behavioral but also non-college educated). We find that such limits can lower both borrowing and default especially in the non-college educated population, which are typically prime regulatory objectives. As their option to smooth consumption becomes impaired, college educated borrowers might default more. Targeted policies still reduce welfare for both types, as the cost of restricting access to credit for some borrowers still exceeds the benefits. This suggests that metrics based on debt and default may provide a misleading guide to the effectiveness of credit market regulations.

Our model explicitly considers two education groups. The results are largely

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

similar for both groups, but there are nuances. For example, higher borrowing costs reduce mistakes for the college-educated but increases mistakes for non-college educated. Welfare effects always go in the same direction, but the magnitude is often quite different. For example, the welfare gains from a small-scale financial literacy education program are three times larger for college educated behavioral agents than for non-college graduates. Finally, some score-dependent policies de-facto only affect non-college educated as essentially all college educated (including over-optimists) have a score above the threshold.

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

A key contribution of this paper is to provide a tractable model of type scoring in consumer credit markets. Our approach circumvents the technical challenges of incorporating asymmetric information into the consumer credit scoring literature (Chatterjee, Corbae, and Ríos-Rull 2008; Chatterjee et al. 2020; Cor-

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

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

bae and Glover 2018; Sanchez 2017; Elul and Gottardi 2015; Livshits, MacGee, and Tertilt 2016; Athreya, Tam, and Young 2012). To characterize equilibrium, Chatterjee et al. (2020) add unobservable extreme-value shocks to households' utility functions to introduce noise that renders perfect screening contracts impossible. Other authors assume that scores can only take two values (Athreya, Tam, and Young 2012), or rule out certain types of screening contracts (Sanchez 2017). By assuming behavioral and rational agents have the same beliefs (and thus preferences over available contracts), we provide a theory of type scoring *without* adverse selection. Our approach results in perfect "mimicking," as over-optimists make precisely the same choices as their rational peers (conditional on their observed state). This perfect "mimicking" implies that screening contracts are not effective. In addition, the pricing of credit over the life-cycle reflects a learning channel as lenders update their beliefs about a borrower's type. This allows us to tractably incorporate credit scoring into a quantitative life-cycle model of consumer credit. The pooling of borrowers (conditional on observables) implies that equilibria in our model yield the largest amount of cross-subsidization (within type-score bins).

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

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

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

The remainder of the paper is organized as follows. We describe our model in Section 2 and simplify it in Section 3 to make some theoretical points. The calibration is described in Section 4 and Section 5 reports the main quantitative results on how type scores evolve and how over-optimists affect credit markets. Section 6 analyzes the impact of several regulatory policies. In Section 7, we consider type-score-dependent policies. Section 8 discusses how our findings relate to the broader debate on consumer credit regulation in unsecured credit markets. Section 9 concludes.

2 Model Environment

The model incorporates over-optimistic 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. The population is composed of two education groups, college and non-college, denoted by $e \in \{C, N\}$. A fraction λ_e of households in each education group have over-optimistic beliefs about the idiosyncratic uncertainty they face, while $(1 - \lambda_e)$ have realistic (correct) beliefs. We assume over-optimistic consumers face worse transitory income risk but incorrectly believe that they face the same risk as realists.[10] Consequently, both types of consumers (within each education group) have identical beliefs about the distribution of transitory income shocks.

We examine a small open economy where the risk-free interest rate is exogenous.[11] Markets are incomplete as the only financial instruments are one-period bonds. Default makes debt partially state-contingent. Debt is priced endogenously by competitive lenders who observe the history of consumers' income and expense shocks.[12] While lenders know the fraction of over-optimists in each education

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

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

[12]Our model is intended to capture key features of revolving credit contracts (such as credit

group, λ_e, and observe the education level of a customer, they cannot directly observe a consumer's type. Thus, lenders form beliefs about borrowers' types, which we term *type scores* and update these beliefs each period, based on consumers' realized income shocks. The bond-price schedule offered to a consumer reflects the expected default risk and, thus, depends on the type score.

At the beginning of each period, income and expense shocks are realized. Lenders observe these realizations and update type scores. Consumers then decide whether to file for bankruptcy and, if they do not file, how much to borrow or save.

2.1 Households

Consumers of both education groups, college-educated $e = C$ and non-college educated $e = N$, maximize their expected discounted lifetime utility,

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

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

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

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

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

cards) which generally allow borrowers to pay existing balances without penalty and to switch lenders. This is broadly consistent with the repricing of debt by competitive lenders in our model.

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

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

$$y_j^{eT} = h_j^e z_j^e \eta_j^{eT}, \tag{3}$$

where h_j^e is the life-cycle component and z_j^e is a persistent autoregressive earnings shock characterized by $\ln z_j^e = \rho^e \ln z_{j-1}^e + \varepsilon_j^e$ with $\varepsilon_j^e \sim N(0, \sigma_{\varepsilon,e}^2)$. Both differ for college vs. non-college graduates. Finally, η_j^{eT} is a transitory earnings shock that is drawn from education e and type T dependent distributions.

2.1.1 Rational and Behavioral Consumers

Rational and behavioral consumers differ along two dimensions. First, consumers differ in the transitory income risks they face. Behavioral agents face more downside risk due to a higher probability of low realizations of the transitory income shock η. Second, behavioral agents are not aware of their worse income risk, as they believe they face the same distribution of transitory income shocks η as realists. Formally, we assume that all consumers have a dogmatic prior that they face the same (good) income shock process. Hence, behavioral consumers are over-optimistic about their transitory income risk.[13]

This model specification of over-optimism is essential for making the model analytically tractable. Since behavioral agents are convinced they are realists, they make the same decision as a rational agent in any given state. Thus, there is no

[13]This is consistent with our empirical analysis using the SCF, see Section 4 and Appendix A.1 for details, as well as the findings in (Balleer et al. 2021).

way for a lender to separate ("screen") types.[14]

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

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

where $\mathbb{E}$ is the true mean and $\mathbb{E}^T$ denotes the subjective expectation of type T. In the above notation, we suppressed education for simplicity. All arguments apply equally to both education groups.

2.1.2 Bankruptcy

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

$$c_j = y_j^{eT} - \gamma \max\{y_j^{eT} - \underline{c}, 0\}, \tag{5}$$

where $\gamma \max\{y_j^{eT} - \underline{c}, 0\}$ is the financial cost associated with bankruptcy.[16] After a bankruptcy, creditors have no claims on a filer's future income or assets, as is the case after a Chapter 7 filing.

[14]Over-optimistic consumers have a dogmatic prior and do not update their beliefs as they age. They interpret bad transitory income realizations as bad luck, which can also befall rational agents. However, they understand that lenders use all available information to update their beliefs (type scores). Abstracting from learning is consistent with Mueller and Spinnewijn (2023) who document that the unemployed are over-optimistic about job finding rates and do not update their beliefs as they remain unemployed.

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

[16]This represents filing costs and the good faith effort required from borrowers to repay their debt. To capture that the good faith requirements take into account a borrower's ability to repay, we introduce an exemption level $\underline{c}$.

2.2 Financial Intermediaries

Financial intermediaries are competitive and can borrow and save at the exogenous risk-free rate r^s. When lending to households, they incur a proportional transaction cost, τ. Lenders offer each borrower a personalized bond-price schedule, which depends on the face value to be repaid next period, d'. Intermediaries take into account expected losses from default when determining this schedule, $q_e(d', \cdot)$. It depends on the borrower's age, j, and education, e, the current realization of the persistent income state, z, the amount borrowed, d', and the lenders' perception of the borrower's type, T. The latter is summarized by a *type score*, s.[17]

Type scores represent the probabilities that intermediaries attach to a household being rational. Although intermediaries cannot directly observe a household's type (i.e., realist or behavioral), they can observe the history of the household's realizations of transitory income shocks, η. Type score s thus summarizes the lenders' posterior belief of a borrower's type. In our framework, type scores are public, all lenders and borrowers observe them.[18]

Type scores are updated using Bayes' rule. All households enter the economy with the informed prior $s_0^e = 1 - \lambda_e$. The prior depends on education to allow for different fractions of behavioral agents within each educational group. At the beginning of each period t, after shocks are realized, the type score is updated using the prior s_{t-1}^e and the shock realizations η_t to update:

$$s_t^e(\eta_t, s_{t-1}^e) = \frac{s_{t-1}\text{Prob}^{eR}(\eta_t)}{s_{t-1}\text{Prob}^{eR}(\eta_t) + (1 - s_{t-1})\text{Prob}^{eB}(\eta_t)}. \tag{6}$$

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

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

[18]As we assume perfect competition, we abstract from lenders generating private information about their customers. Johnen (2020) shows that private information about naïvité can endogeneously create market power. Lenders learn which are their most profitable borrowers and aim to retain them.

are the same as those of a rational household.

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

2.3 Equilibrium

Perfect competition and free entry result in lenders earning zero expected profits on each loan. Conditional on observable characteristics (persistent income z, education e and age j) and a household's type score (s), bond-price schedules are determined by the default probability of a household $\theta^e(d', z, j, s)$ and the risk-free rate. Upon default, a fraction γ of income in excess of the exemption $y' - \underline{c}$ is garnished and unforeseen expenditures κ are settled first. Banks recover the remainder. Thus, the total fraction of $\max\{\gamma(y' - \underline{c}) - \kappa, 0\}/d'$ of the loan's face value is recovered through garnishment.[19]

The zero profit condition implies a bond-price schedule of

$$q_e^{ub}(d', z, j, s) = (1 - \theta^e(d', z, j, s))\overline{q} + \theta^e(d', z, j, s)E\left(\frac{\max\{\gamma(y' - \underline{c}) - \kappa', 0\}}{d'}\right)\overline{q}, \quad (7)$$

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

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

Consumers take the equilibrium bond-price schedule as given, as well as how lenders update type scores and interest rates following transitory income shock

[19] This convention differs from that in Livshits, MacGee, and Tertilt (2007, 2010), where the garnisheed income was split proportionately between the lender and the expenditure shock. The current formulation eliminates the ex-ante incentive of the borrower to inflate the face value of the debt in order to increase the lender's ex-post share of the proceeds from the garnishment.

realizations.[20] The households' optimization problem is summarized by a value function V, which is the value of not defaulting, while $\overline{V}$ is the value of filing for bankruptcy. Since bankruptcy cannot be declared in consecutive periods, we define the value of delinquency, $\widetilde{V}$, for households ineligible for bankruptcy.[21] 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 the education group $e \in \{C, N\}$ and behavioural type, $T \in \{R, B\}$:

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

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

$$\begin{aligned} \widetilde{V}_j^{eT}(z, \eta, \kappa, s) =& \; u\left(\frac{c}{n_j}\right) + \beta \mathbb{E}^T \max\left\{ V_{j+1}^{eT}(d', z', \eta', \kappa', s'), \overline{V}_{j+1}^{eT}(z', \eta', s') \right\} \\ &\text{s.t. } c = y_j^{eT} - \gamma \max\{y_j^{eT} - \underline{c}, 0\} \\ &\quad\;\; d' = (\kappa - \gamma \max\{y_j^{eT} - \underline{c}, 0\})(1 + r^r). \end{aligned} \tag{11}$$

An equilibrium is a set of value functions, optimal decision rules for consumption $c(\cdot)$, debt levels $d'(\cdot)$ and default, default probabilities $\theta^e(\cdot)$, and bond prices $q_e^b(\cdot)$, 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.

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

[21] Our notion of delinquency addresses the possibility of empty budget sets for a consumer who is ineligible for bankruptcy but draws a large expense shock. The only debt in this case is the expense shock. Since delinquency is both unattractive (entailing all the costs of bankruptcy without the benefit of discharging debt) and the likelihood of a large expense shock is low, only 0.04% of bankruptcy filers transition to delinquency in our benchmark calibration. This is fewer than the number impacted by the large expense shock. Delinquency in our model is thus quite different from the more common use of delinquency to refer to being a few months late on a payment.

2.4 Welfare Measures

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

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

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

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

3 Default and Over-optimism

Our quantitative model provides a rich environment to investigate the pricing of defaultable debt and consumer protection policies when lenders cannot directly observe a consumer's type. To illustrate some of the key forces, we analyze a two-period example with risk-neutral borrowers. Although risk neutrality removes the intensive margin of (over) borrowing, by simplifying the algebra, it clearly shows how the pricing of default risk by competitive lenders shapes cross-subsidization.

As in our quantitative model, the 2-period endowment economy is populated by measures λ of over-optimistic and $(1-\lambda)$ of rational consumers. We assume that the second-period endowment of over-optimists is uncertain. To tractably capture the effect of type-scores from our quantitative model, we assume that competitive lenders cannot distinguish types but have (binary) signals about underlying types which they use to price default risk. To capture learning over the life-cycle (cf. our quantitative results in Section 5), we vary the precision of these signals.

Our stylized example illustrates how default risk shapes several features of unsecured consumer credit. We show that equilibrium default combined with the partial pooling of types who differ in their income risk results in cross-subsidization. Since over-optimists are higher risk than rational borrowers, over-optimistic borrowers are cross-subsidized by rational borrowers. Our example also shows that, from the perspective of a social planner facing the same technological and informational constraints as borrowers and lenders, inefficient over-borrowing can occur for some parameters. This opens up the possibility that consumer protection regulation could improve welfare. Our example highlights the challenges posed by imperfect information about a consumer's type when a borrower can default: regulation that limits access to credit can impact cross-subsidization and have differential impact across types.

These qualitative insights point to key mechanisms in our quantitative analysis in Section 5. Importantly, they also highlight the need for a quantitative model for policy analysis to assess the welfare implications of consumer protection regulation with the partial pooling of realists and overoptimists.

3.1 Two-Period Endowment Economy

Consumers are risk neutral with preferences represented by

$$u(c_1, c_2) = c_1 + \beta E(c_2 - \delta\chi) \tag{13}$$

where $c_t \geq 0$ denotes consumption in period t, β is the discount factor, δ is an indicator that takes the value of one if a consumer defaults, and χ is the cost of default. Consumers take the bond price schedule quoted by lenders $q(\cdot)$ as given and can borrow to transfer resources across time: $c_1 = y_1 + q(d)d$ and $c_2 = y_2 - (1-\delta)d$, where d is the face value of debt.

In period 2, consumers' income is stochastic $y_2 \in \{y_l, y_h\}$. Rational consumers, who comprise fraction $(1-\lambda)$ of the population, face no income risk as they receive y_h with certainty in period 2. Although over-optimists believe their probability of y_h is 1, their true probability of receiving the high endowment is $\omega < 1$.

Consumers can declare bankruptcy in period 2. In this case, they do not repay their debt but face a utility cost of default, χ. In our two-period two-state economy, this utility cost provides a flexible way of capturing various costs, including the loss of a fraction of the endowment. This gives rise to endogenous borrowing limits as the default risk affects the bond price $q(d)$ and thus the amount received by the consumer $q(d)d$. With this default cost, there is no recovery for lenders in the event of default, which simplifies the pricing of debt.

Lenders are competitive and can borrow and save at the exogenous risk-free rate $r^s = 0$. This implies that the risk free bond price ($\bar{q}$) equals 1. Lenders offer each consumer a personalized bond-price schedule, which depends on the face value to be repaid next period, d, and their prior of the borrower's type, summarized by a type-score, s. The equilibrium bond price schedule $q(d,s)$ is simply equal to the probability of a borrower with type-score s repaying a loan of size d.

3.2 Insights From the Simple Example

We first examine the case where lenders do not receive a signal of a borrowers type but know the fraction of over-optimists λ. A borrower defaults whenever d exceeds their willingness to repay (i.e., $d > \chi$) or their ability to repay (i.e., $d > y_2$). In the latter case, the borrower defaults even if the default cost χ exceeds the value of debt. The *risky loan* (which sees default in equilibrium) is thus $d = \min\{\chi,\ y_h\} > y_l$.[22] This risky loan is repaid whenever $y_2 = y_h$, i.e., by realists and over-optimists with the high realization of the endowment. The *risk-free loan* is $d = \min\{\chi, y_l\}$.

Proposition 3.1. *If an equilibrium features borrowing using the risky loan, then there is cross-subsidization from rational to over-optimistic borrowers. Otherwise (if borrowing takes place via the risk-free loan or consumers choose not to borrow), there is no cross-subsidization in equilibrium.*

Proof. Cross-subsidization occurs if and only if there is positive probability of default in equilibrium.[23] If there is no default risk, both borrower types face the same actuarially fair bond price $q = 1$. In contrast, since the risky loan pools rational and overoptimistic borrowers, it's price $q = \lambda\omega + (1-\lambda)$ is strictly between the actuarially fair price for rational borrowers (1) and that for over-optimists (ω). □

[22]With linear utility, if consumers choose the risky loan they prefer the largest face value offered.

[23]If markets are complete, i.e., if repayment of loans is contractually income-dependent, then there is no default in equilibrium, but there may be some cross-subsidization as borrowers of different types are still pooled and prices of Arrow securities reflect the *average* probabilities of the underlying income realizations. Such cross-subsidization would still tend to go from realists to over-optimists, since the latter would be selling high-income-state Arrow securities at higher than actuarially fair prices and buying low-income-state securities at prices lower than actuarially fair.

This proposition illustrates that cross-subsidization occurs whenever a loan is defaulted on with positive probability by borrowers with heterogeneous default probabilities. The direction of cross-subsidization is determined by whether a borrower type defaults more or less often than the average for the group they are pooled with. In our model, since over-optimists face a riskier income process that leads them to default more often than rationals, when over-optimists are pooled with rationals they are cross-subsidized.

We define *inefficient over-borrowing* as borrowing that the constrained social planner would not undertake. Formally, consider a paternalistic social planner that maximizes the weighted average of utilities $\lambda u^B(c_1, c_2) + (1-\lambda)u^R(c_1, c_2)$ subject to the technological (including informational) and participation constraints. Thus, the planner cannot directly transfer resources between agents but has access to the same intertemporal lending market and information as lenders.

For simplicity, assume the lower endowment realization is zero, $y_l = 0 < y_h$, which eliminates the possibility of risk-free borrowing. In this case, borrowers choose between the risky loan at the pooled price $1 - \lambda(1-\omega)$ and not borrowing at all. They choose to borrow when $1 - \lambda(1-\omega) \geq \beta$.

Proposition 3.2. *Inefficient over-borrowing by over-optimists is possible only when there is positive probability of default in equilibrium and the default costs exceed the income realization in the state where default does not occur, i.e.,* $\chi > y_h$.

Proof. When deciding whether to borrow, consumers compare the value of consuming qd with the perceived discounted cost of their repayment βd. Over-optimists make two opposing mistakes that bias the perceived cost of borrowing: while they do not take into account the default costs, they over-estimate the probability that they will repay the loan. Overoptimists overestimate the expected value of what they repay by $(1-\omega)d$ since they believe they receive y_h with certainty. However, they underestimate the expected value of default costs $(1-\omega)\chi$. So long as $\chi \leq y_h$, and thus $d = \chi$, these two mistakes exactly offset. Thus, the social planner and the borrowers choose the same allocation when $\chi \leq y_h$. However, when $\chi > y_h$ (and the equilibrium risky loan is $d = y_h$), over-optimists underestimate the default cost by more than they overestimate repayment. As a result, inefficient over-borrowing by over-optimists can occur (only) when $\chi > y_h$.[24] □

[24] The pooling of over-optimists and rational borrowers seemingly makes overborrowing more

Corollary 3.3. *Banning risky borrowing is welfare-improving for some parameter values.*

Proof. For welfare to (strictly) increase when risky borrowing is banned, the losses from inefficient borrowing must exceed the gains from borrowing (net of cross-subsidization) for rational borrowers. This holds when there are sufficiently many behavioral borrowers, when the borrowers are sufficiently impatient to borrow at (pooled) actuarially-fair prices, and when the cost of default $\chi > y_h$ is sufficiently large to yield inefficient over-borrowing by over-optimists. □

The inefficiency discussed above adds to other welfare losses due to incomplete information. The pooling of realists and overoptimists can result in lower welfare than in the full information case, where lenders (and the planner) can identify a consumers type. Even without an intensive margin of borrowing, cross-subsidization can make borrowing unattractive for consumers, leaving the welfare of realists lower than if lenders could identify their type. Since the planner has the same information as the lenders, they cannot address any possible welfare losses arising from incomplete information. This foreshadows a challenge facing consumer protection regulation in our quantitative experiments.

3.2.1 The Role of Information

In the quantitative model, lenders form beliefs over a borrower's type which evolve with the realization of income shocks. To examine the implications of lenders beliefs for limiting access to credit, we analyze the welfare implications of changes in the accuracy of lender's priors in the 2-period example. We show that consumer protection regulation that differentially restricts borrowing based on type-scores can be welfare-improving for some parameter values.

We start by introducing binary signals, r or b, with precision π about the borrowers' types into our example: $\text{Prob}(T = R|\sigma = r) = \text{Prob}(T = B|\sigma = b) = \frac{1+\pi}{2}$. For lenders, these binary signals create two subpopulations that differ in their share of rational borrowers, ie, *type-scores*, $s_i, i \in \{r, b\}$ where $s_r = \frac{(1-\lambda)\frac{1+\pi}{2}}{(1-\lambda)\frac{1+\pi}{2}+\lambda\frac{1-\pi}{2}}$ and $s_b = \frac{(1-\lambda)\frac{1-\pi}{2}}{(1-\lambda)\frac{1-\pi}{2}+\lambda\frac{1+\pi}{2}}$. The precision of the signal changes the type share in each

likely as it results in overoptimists being cross-subsidized by rational borrowers. Since there is no intensive margin of borrowing, the overoptimists' mistakes exactly offset when $\chi \le y_h$. Thus, even with cross-subsidization, if there is risky borrowing in equilibrium, it can be inefficient only when $\chi > d = y_h$.

pool without changing the overall population of the types. When the signals have no precision ($\pi = 0$), the two sub-populations are identical: $s_r = s_b = 1 - \lambda$. As precision improves, the type-score of the r-population improves, while that of the b declines. With perfect precision $\pi = 1$, the pools perfectly separate types: $s_r = 1$ and $s_b = 0$.

We first consider the case where there is no borrowing when signals are uninformative: $1 - \lambda(1 - \omega) < \beta$.[25] If $\chi \leq y_h$, ex-ante (paternalistic) welfare is weakly increasing in the precision of the signal. It is flat until we reach a point where the r signal results in sufficiently favourable bond prices that consumers choose to borrow. From that point on, welfare increases in signal precision as the increase in the fraction of rational borrowers leads to lower deadweight loss. To see this, consider replacing an overoptimist with a realist in the pool. Although both types believe they have the same value of borrowing, an overoptimist will default with probability $1-\omega$ and incur default cost χ.[26] Here improvements in "credit scoring" (signal precision) act to (correctly) exclude over-optimists from risky borrowing.

We now examine the case where there is borrowing in equilibrium with uninformative signals (i.e, the pooling case) but where perfectly informative signals lead to exclusion of B-borrowers: $1 - \lambda(1 - \omega) \geq \beta > \omega$, and $\chi > y_h$ (i.e., inefficient overborrowing is possible). Ex-ante (paternalistic) welfare is weakly increasing in the precision of the signal. It is flat until we reach a point π^*, above which consumers with the b signal face prices lower than they are willing to accept, $q_b = (s_b + (1 - s_b)\omega) < \beta$, and thus choose to not borrow. At π^*, ex ante welfare improves discontinously, as b-borrowers who were inefficiently overborrowing (on average) drop out. From then on, welfare increases as fewer behavioral borrowers receive the r signal and fewer rational borrowers receive the b signal.

When $\beta \leq \omega$, even perfectly precise signals do not result in the exclusion of over-optimists from borrowing, since they choose to borrow even when their loans are not cross-subsidized. This may be the case even when a social planner would like to exclude over-optimists from the credit market, i.e., when they are inefficiently over-borrowing. This brings an important refinement of Corollary 3.3:

Corollary 3.4. *Banning risky borrowing for consumers with signal b can be welfare-*

[25] This condition states that prices are too low for consumers to borrow, cf. Section 3.2.

[26] The number of borrowers may or may not be increasing (depending on whether λ is greater or smaller than $\frac{1}{2}$).

improving, even when the ban for all borrowers reduces welfare. If a total ban on risky borrowing improves welfare, then so does the ban for borrowers with signal b*.*

Note that any borrowing ban can only be welfare-improving when over-optimists inefficiently over-borrow ($\chi > y_h$ is a necessary condition for that in our example).

The last proposition illustrates the motivation for consumer protection policies that target segments of the population with low type scores. We investigate the quantitative effects of such policies in Section 7. In our dynamic model, these policies may have additional costs if they restrict borrowers whose type-scores drop after negative income shocks and are thus in need of income-smoothing loans.

3.3 Linking the Theoretical Insights to our Quantitative Model

Our stylized two period example illustrates several key features of our quantitative model. First, it shows how our assumption that behavioral and rational agents have the same beliefs eliminates adverse selection as it results in perfect "mimicking" since over-optimists make precisely the same choices as their rational peers (conditional on their observed state). Despite differences in default risk, our assumption that both types have identical beliefs about their income processes implies that lenders cannot design a separating contract.

Second, in equilibrium, rational borrowers generally cross-subsidize behavioral borrowers. As in the two period example, cross-subsidization in our quantitative model is driven by the partial pooling of types and behavioral borrowers having higher default rates. Similarly to our example, the higher default rates of behavioral borrowers are due to their facing a higher probability of adverse income shocks than rational borrowers. Since adverse shocks increase the probability of bankruptcy, behavioral borrowers generally default more often than rational agents.

One feature that is more challenging to map directly between our two-period and dynamic models is the cost of over-borrowing. In the two period model, over-optimists underestimate the cost of default. In the dynamic model, over-optimists face both the costs associated with default and from distorting intertemporal consumption. In the dynamic model, we decompose these mistakes into overborrowing and filing too late. Similar to our two period example, over-optimists underestimate these costs while overestimating the probability of repaying their debt.

4 Benchmark Calibration

Since much of the policy discussion surrounding behavioral consumers and consumer financial protection is recent, our benchmark calibration targets data from the 2016 SCF and aggregate data over 2013-2017.[27] Our calibration first sets several parameters and then calibrates the remaining parameters to match data moments.

4.1 Externally Calibrated Parameters

Consumers enter the economy at age 20 and live for 54 years over 18 three-year periods. For the first 15 periods, consumers earn stochastic (labor) income. During the last three periods, consumers receive non-stochastic retirement benefits. The felicity function is $u(c) = \frac{(c/n_j)^{1-\sigma}-1}{1-\sigma}$. We set the coefficient of relative risk aversion to $\sigma = 2$. For n_j, we follow Livshits, MacGee, and Tertilt (2007) and use their household size life-cycle profile in equivalence scale units.[28]

We set the annual risk-free interest rate at $r^s = 1\%$.[29] The rate on delinquent debt (r^r) is fixed at 20% per year as in Livshits, MacGee, and Tertilt (2007).

We parameterize the expense shocks to U.S. estimates of medical expenses, divorces, and unplanned parenthood.[30] The support of expense shocks, K, has three elements: $\kappa \in K = \{0, \kappa_1, \kappa_2\}$. The smaller shock is 26.4% of average three-year income. The large shock corresponds to 82.18% of the average three-year income. The probabilities $[\pi_1, \pi_2]$ of these shocks are 7.1% and 0.46%, respectively. Expense shocks are assumed to hit only working-age households.

Consumers are born with college or non-college education. The share of college educated ($e = C$) households is 38% which is the fraction of the U.S. population with a Bachelor's, Master's, Professional or Doctoral degree according to the Educational Attainment in the United States Data (U.S. Census 2021). We classify the

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

[28] See the working paper Livshits, MacGee, and Tertilt (2003) for details on the profile. We updated the life-cycle profiles with recent U.S. Census Bureau data and found little change in the last three decades.

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

[30] We follow Livshits, MacGee, and Tertilt (2007), whose expense-shock process was based on data from the mid-1990s. Over the last three decades, medical out-of-pocket spending as a fraction of median household income has remained stable, as has the number of births per 15-44 year-old women. While the number of unwanted births rose slightly, this has been offset by a slight decline in divorces per 1,000 population.

remainder of the population as non-college educated ($e = N$).

In our model, the two education groups differ in their life-cycle earning profiles as well as in their education-specific persistent and transitory labor income processes (see Equation (3)). We obtain education-dependent statistics of average life-cycle income growth and persistent risk from Hubbard, Skinner, and Zeldes (1994) by matching college educated individuals to the 16+ years education group and non-college educated individuals to 12-15 years of education. Retirees receive a deterministic pension of 20% of the average income in the economy, plus 35% of their final persistent income. A five-state Markov process represents persistent income risk. The parameters of this process map into an autocorrelation of $\rho_N = 0.946$ and $\rho_C = 0.955$ for non-college and college and variances of innovation of $\sigma^2_{\varepsilon,N} = 0.025$ and $\sigma^2_{\varepsilon,C} = 0.016$, respectively.[31]

Within each education group, we need to parameterize a transitory shock process for behavioral and rational people. As behavioral types are unobservable, there is no direct way to estimate these processes separately. Instead, we adopt an average transitory income process from the literature (specifically, we use the triennial process from Livshits, MacGee, and Tertilt (2010)) and then split the aggregate transitory shock into two processes. The transitory shock can take three values: $\eta \in [\eta_1, \eta_2, \eta_3]$. On average (including behaviorals and rationals), 10% of households receive a low and high transitory income shock each period. The support is set to match a triennial variance of $\sigma^2_\eta = 0.05$.

Over-Optimism

Our calibration strategy targets two parameters related to behavioral agents: the fraction of behavioral agents in their education group, λ_e, and their degree of over-optimism (defined below). We use data from the 2016 and 2019 SCF to pin down these parameters.

We assume that behavioral agents are those with low financial literacy. Specifically, we classify as behavioral households those that answered at most one of three simple financial literacy questions correctly. Not surprisingly, this yields

[31] These values for education specific persistent income processes are consistent with average processes estimated in Storesletten, Telmer, and Yaron (2004) and Carroll and Samwick (1997). We map annual values into triennial values and employ the Tauchen method (cf. Adda and Cooper (2003)) to discretize income shocks. See Appendix A.2 for details on the life-cycle component of labor earnings.

a higher share of behavioral agents amongst those with lower education levels. Amongst the non-college educated, we find a fraction $\lambda_N = 31\%$ of behavioral agents, whereas that fraction is only $\lambda_C = 15\%$ amongst college educated individuals. See Appendix A.1 for further details.

Over-optimists differ from rational people only in their transitory income process. Our calibration further assumes that they face the same shock magnitudes η_1, η_2, η_3 and differ only in the probabilities. We define the degree of over-optimism as the ratio of the probability of a low transitory income realization of the two types of agents: $\text{Prob}^B(\eta_1)/\text{Prob}^R(\eta_1)$. We calculate this ratio (ψ_e) for each education group as follows. We use an SCF question that asks respondents whether their income is higher, lower, or the same as that of a usual year. Consistent with our model of over-optimism, more households report their income is lower than usual rather than higher (see Table A1). Respondents we classify as behavioral (due to a low score on the financial literacy questions) are $\psi_N = 1.28$ or $\psi_C = 1.29$ times more likely to report a "lower than usual" income when non-college or college educated. These values are remarkably close, and consequently we set $\psi = 1.285$ for both education groups. Given ψ, λ_C, λ_N and the transitory income process discussed above, we derive the shock probabilities for rational and behavioral people (see Table 1 and Appendix A.1).

To summarize, our calibration replicates the data in that education is correlated with the likelihood of being over-optimistic but not the magnitude of that bias. While the degree of over-optimism of behavioral agents is virtually the same between non-college and college educated individuals, the share of behavioral people is nearly double amongst people without a college degree. Furthermore, our modelling assumption that behavioral people have incorrect beliefs *and* have lower income as they experience negative income shocks more often is supported by the data. Respondents who we classify as behavioral due to their low financial literacy in the SCF report more negative surprises about their income (see Table A1). According to our modelling assumption, more negative surprises must also result in lower average income. This is a testable assumption. Indeed, we find that financial literacy is highly positively correlated with income in the SCF, even after controlling for college education. See Appendix A.1 for details.

Table 1: Transitory Income Shock Process

		η_1	η_2	η_3
Probabilities:				
Non-College	Rational	9.19%	80%	10.91%
Non-College	Behavioral	11.81%	80%	8.19%
College	Rational	9.59%	80%	10.41%
College	Behavioral	12.32%	80%	7.68%
Aggregate		10%	80%	10%
Magnitudes:		0.59	0.98	1.57

Notes: These are triennal numbers. The aggregate process is taken from Livshits, MacGee, and Tertilt (2010) (with $\mu_\eta = 1$ and $\sigma^2_\eta = 0.05$). The ratio of downside risk between rational and behavioral determines the degree of over-optimism, see text and Appendix A.1.

4.2 Internally Calibrated Parameters

The remaining five parameters—the discount factor β, the income exemption during bankruptcy $\underline{c}$, the fraction of income above the exemption garnished during bankruptcy γ, the interest rate ceiling $\overline{r}$, and the transaction cost of lending τ—are chosen to target six data moments. These moments are calculated primarily using data described in Exler and Tertilt (2020) and summarized in Table 2.[32]

We target a ratio of (gross) unsecured debt to total earnings of 6.69%. This measure uses the average over 2013 and 2017 of revolving credit from the Federal Reserve Board of Governors G.19 series divided by personal disposable income from the National Income and Product Accounts. The target for filings of 0.45% is the average over 2013 and 2017 of the fraction of consumers declaring Chapter 7 bankruptcy. For each year, this is calculated by dividing total Chapter 7 filings, reported by the American Bankruptcy Institute, by the number of households reported in the Census Bureau's Current Population Survey.

Following Exler and Tertilt (2020), the average real borrowing interest rate over 2013-2017 is 10.6%. They construct this estimate using nominal interest rates on

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

Table 2: Internally Calibrated Parameters

Parameter		Value	Target	Data	Model
Discount factor	β	0.98	Debt-to-earnings	6.69%	6.54%
Exemption in bankruptcy	$\underline{c}$	0.24	Bankruptcy filings	0.45%	0.56%
Recovery in bankruptcy	γ	0.82	Charge-Offs	3.30%	2.09%
Transaction cost Lenders	τ	6.93%	Avg Borrowing r	10.60%	10.40%
Interest rate ceiling	$\overline{r}$	53.89%	CV of Borrowing r	0.54	0.53
			Share Borrowers	28.4%	26.6%

Notes: Based on data series described in Exler and Tertilt (2020). CV is Coefficient of Variation. Although the model period is three years, the data and model targets are annualized.

personal loans and credit cards net of the one-year ahead CPI inflation.[33] The average charge-offs during that period are 3.3%.[34]

Finally, we target the dispersion in borrowing interest rates and the fraction of borrowers. Exler and Tertilt (2020, Table 4) calculate the coefficient of variation from interest rates on loans that carry a positive balance, which in the 2016 and 2019 SCF averaged 0.54. The fraction of borrowers combines two observations: Exler and Tertilt (2020) report that 71% of households in the SCF report having a credit card. However, not all credit card owners use it to borrow, especially over a longer time (since our model periods are three years). According to Adams and Bord (2020, Section 3.1), 40% of credit card accounts are "heavy revolvers," a measure we use to estimate the fraction of borrowers at $71\% \times 40\% = 28.4\%$.[35]

We choose β, $\underline{c}$, γ, τ, and $\overline{r}$ to minimize the sum of the squared relative residuals between the model and the data moments. Although somewhat understating default premia and overstating defaults, the over-identified calibration matches the data well.[36] Our calibration yields an annual discount factor $\beta = 0.981$, an income exemption in bankruptcy of $\underline{c} = 0.237$, above which lenders recover $\gamma = 82.2\%$ of bankrupts' income, the transaction cost in lending is $\tau = 6.93\%$, and the interest

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

[34] 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.

[35] The SCF also asks people whether they carry a balance on a card. The number for 2016 is 39%, suggesting that roughly three-quarters of those carrying a balance are heavy revolvers.

[36] In equilibrium, the model sees lower-income non-college educated borrowers defaulting on modest debts. This drives up the bankruptcy rate but depresses default premia, as write-offs on those loans are small.

rate ceiling is $\overline{r} = 53.89\%$.[37] Although the model moments depend jointly on the parameters in a non-linear fashion and our calibration is overidentified, 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 and the fraction of people borrowing, the level of exempt income drives average cost of bankruptcy and thus the frequency of default, the bankruptcy recovery rate changes the risk premium and, together with the transaction cost of lenders, drives the average borrowing interest rates, while the interest rate ceiling limits the coefficient of variation of borrowing interest rates.

5 Behavioral Mistakes and Cross-Subsidization

Our calibrated economy illustrates several interesting insights that arise in an environment with both behavioral and rational agents. While it is not surprising that behavioral borrowers *overborrow*, what is less intuitive is that they also *file too late* for bankruptcy. These mistakes reflect both incorrect beliefs and the *cross-subsidization* of behavioral borrowers by rational borrowers. As shown in our stylized two-period model in Section 3, this cross-subsidization results from the pooling of types with heterogeneous default risk and generally sees behavioral (rational) borrowers paying lower (higher) rates than would be actuarially fair in an economy with full information about each borrower's type. These forces will play a key role in our examination of consumer protection policies in Section 6.

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

[37]The resulting interest ceiling is larger than implied by current usury laws. However, official legal ceilings can often be avoided. This ceiling is nonbinding for almost all households in our experiments. As noted in Livshits, MacGee, and Tertilt (2010), having no ceiling can lead to a (very) small number of people borrowing large amounts at very high interest rates (with little intention of repaying them), which results in artificially high average interest rates and variance. The calibrated cost of lending, τ, is not that far off the estimates of credit card operational and reward costs reported in Agarwal et al. (2018).

Table 3: Equilibrium Outcomes Across Types

	No College		College		**Aggregate**
	Realists	Behavioral	Realists	Behavioral	
Debt-to-earnings	6.4%	7.8%	6.0%	7.6%	6.54%
Filings	0.78%	0.91%	0.12%	0.16%	0.56%
Interest Rates	11.7%	11.8%	8.7%	8.8%	10.40%
Fraction borrowing	30%	33%	19%	22%	26.59%
Filing too late		0.04%		0.08%	0.05%
Overborrowing (as share of debt)		6.66%		9.78%	7.85%

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

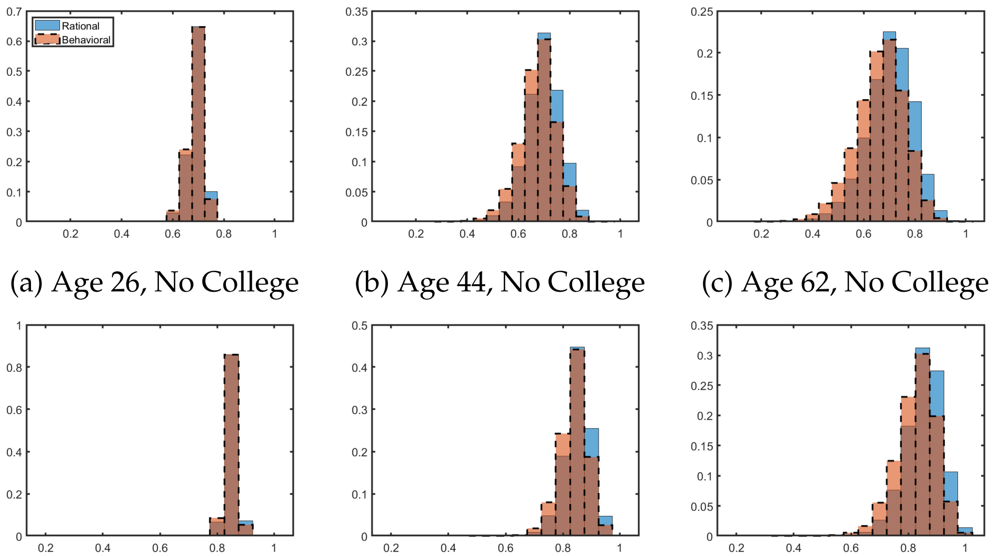
5.1 Benchmark Outcomes

Our baseline calibration implies significant differences in borrowing and filings between rationals and behaviorals (see Table 3). Behavioral consumers in both education groups borrow more than rationals, default more frequently, and on average pay higher interest rates. The presence of behaviorals matters for aggregates: they drive up the overall debt-to-earnings ratio, filings, and the average interest rate. Moreover, behavioral consumers' incorrect expectations result in their making systematic financial mistakes. Interestingly, the mistakes are more pronounced for the college educated.[38]

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. Conditional on these scores, lenders quote their credit prices. On the one hand, this implies that there is some pooling of types for each (interior) type score. On the other hand, when type scores become more informative, realists obtain better pricing than behaviorals.

A lender's (informed) prior that a newborn household is rational equals their share within their education group (31% for noncollege and 15% for college). Lenders

[38]The size of mistakes also depends on the degree of over-optimism. Appendix B.1 presents results varying the severity of the wrong priors and the fraction of the population that is behavioral.



(a) Age 26, No College (b) Age 44, No College (c) Age 62, No College

(d) Age 26, College (e) Age 44, College (f) Age 62, College

Figure 1: Distribution of Type Scores (PDF)

update these type scores each period based on a household's realized transitory income.[39] Thus, adverse income realizations can result in declining scores for both realists and behaviorals. Conversely, type scores (weakly) monotonically increase for individuals who do not experience an adverse income shock. Since behavioral agents experience negative income shocks more often than realists, their scores are more likely to decline with age. Even so, a lucky behavioral agent's score can remain high for their entire lifetime, while an unlucky rational can see their score fall dramatically as they age.

Figure 1 depicts the evolution of the distribution of type scores by age for each education group. At age 26, the type-score distribution is clustered near the initial score of 0.69 (for non-college) and 0.85 (for college), as most households have not yet experienced adverse shocks. However, since households that are hit by an adverse (favorable) transitory income shock are more likely to be behavioral (rational), there is some mass below (above) these scores. As households age, the distribution of type scores becomes more dispersed in response to various sequences of realized shocks which results in a "flattening of the density" with age.

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

The flattening of the distribution results in less pooling of types with age. Early in life, the type-score distribution of over-optimists nearly coincides with that of realists (see Figures 1a and 1d). 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 (cf. Figures 1c and 1f). However, even for older consumers, there remains substantial pooling of types, especially for intermediate type scores.

The 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.[40] This pattern is apparent in Figure 2, which plots the distribution of the difference between actuarially fair interest payments with perfect information about the types and the actual equilibrium interest payments, $(q(\cdot) - q(\cdot)_{fair})d$. As the figure shows, essentially all behavioral borrowers benefit from cross-subsidization to varying extents, while rational borrowers pay more due to the presence of behavioral consumers. Although the figure includes both education groups, pooling happens only within groups.

In Table 3 we report two types of financial mistakes by behavioral agents: overborrowing and filing for bankruptcy too late. 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 the agent's past choices (before being informed of their true income risk).

We measure overborrowing as the relative difference between the equilibrium debt held by behavioral agents and the amount they would choose to hold if they were (suddenly) made aware of their true income process. The difference in borrowing between behavioral and rational types reported in Table 3 (7.8% versus 6.4% for non-college and 7.6% vs. 6.0% for college) actually understates the extent of overborrowing, as behavioral borrowers hold on average nearly 8% too much debt relative to their rational selves in the same state facing the same prices.

Although overborrowing by beharioral agents is not surprising, filing too late is less intuitive, especially given that they file more often than rationals (see Table 3). We define "filing too late" as behaviorals who choose not to file for bankruptcy in a given period but would have filed if informed of their true income process. In our calibrated economy, behavioral filings would rise by 4% for non-college and

[40]See Section 3 for a theoretical derivation.

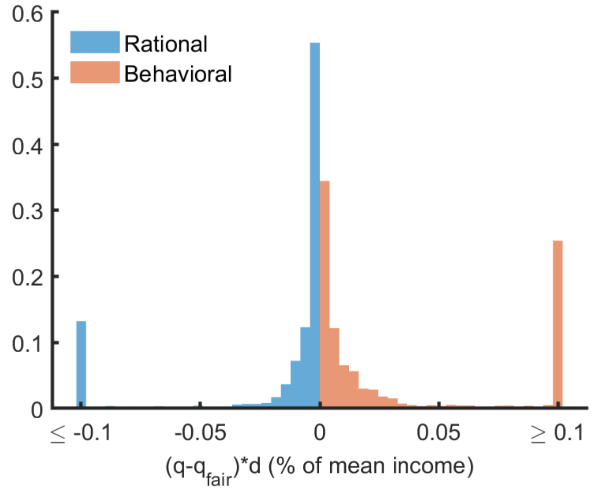


Figure 2: Distribution of Cross-Subsidization (PDF)

Note: This figure joins two separate histograms for rational and behavioral types. Each type's PDF pools both college and non-college educated borrowers and aggregates to one.

by 50% for college educated borrowers in the period when being informed.[41]

Over-optimistic expectations of future income thus generate both a greater desire to borrow and a higher willingness to roll over loans rather than to default right away. Both mistakes arise due to an inaccurately high belief about a behavioral borrower's future ability to repay, but are more pronounced for behavioral consumers with a college degree. Although our main focus is on the interaction and differences between behavioural and rational agents, there are three important differences between education groups: (1) College educated agents have a steeper life-cycle earnings profile. Consequently, the college group has a more pronounced motive to borrow against high prime-age income when young and their debt to income and bankruptcy filings exhibit a stronger life cycle profile. Thus, overestimating one's income has a stronger effect, and overborrowing in the college group is more pronounced. (2) The calibrated bankruptcy costs are pro-

[41]Our measure of "filing too late" (and of over-borrowing) is computed as a one-time "partial equilibrium" exercise based on the ergodic distribution of debts/asset holdings with interest rates fixed at their equilibrium levels. We compute the difference between the decisions taken by behavioral borrowers in equilibrium and those they would have made (at the same asset position facing the same interest rate schedules) if informed of their true income process. This computation is done when the information is revealed. General equilibrium effects are discussed in Section 5.2.

gressive. The combination of progressive bankruptcy cost and higher incomes for the college educated drive lower bankruptcy rates as well as higher average debt levels for college. (3) College educated consumers are less likely to be behavioral and face a worse income process. Thus, pooled equilibrium interest rates will be more favorable and facilitate rolling-over higher debts. Both (2) and (3) amplify the effect of over-optimism on late bankruptcy filings.

5.2 Decomposition

The borrowing and default decisions of behavioral consumers are shaped by three factors: greater downside income risk (which we refer to as “worse risk”), over-optimistic expectations, and cross-subsidized loan prices through the partial pooling of types. To decompose the contribution of each of these factors, we simulate three counterfactual economies and compare them to the outcomes of behavioral consumers in the benchmark economy. Table 4 reports the three counterfactuals alongside the average outcomes of behavioral consumers in the benchmark economy. The share of non-college and college educated individuals is held constant across economies and results are averages across education groups.[42] We start from a counterfactual economy populated solely by realists, i.e. households who face the lower-risk income process, hold realistic beliefs, and face individual loan schedules without cross-subsidization, cf. column (1). Next, we consider an economy populated solely by households with correct beliefs but with the higher risk income process, cf. column (2). The third counterfactual isolates the role of over-optimistic beliefs, as this economy is populated by over-optimists, cf. column (3). Finally, column (4) averages the outcomes for the behavioral consumers from our benchmark economy (cf. Table 3 for separate statistics). Compared to column (3), cross-subsidization through partial pooling is added in column (4).

Comparing columns (1) and (2) shows that greater downside transitory income risk of behavioral borrowers mostly affects repayment behavior. Defaults rise by more than 10% (or 0.08pp) and — through rising risk premia — borrowing interest rates increase by 44 basis points. While worse risk drives up bankruptcy filings, there is little impact on the average debt-to-income ratio and the fraction of total borrowers. Borrowers scale down their debts in line with their lower average

[42] The disaggregated decomposition tables by education groups look qualitatively similar.

Table 4: Decomposing Behavioral Consumers in the Benchmark Economy: Beliefs, Extra Risk or Cross-subsidization?

	(1)	(2)	(3)	(4)
Income process	Better risk	Worse risk	Worse risk	Worse risk
Beliefs	Realistic	Realistic	Over-opt	Over-opt
Pricing	Individual	Individual	Individual	Cross-subsidized
Debt-to-income (DTI)	6.5%	6.6%	7.5%	7.7%
Filings	0.63%	0.71%	0.71%	0.73%
Interest rates	10.79%	11.23%	10.89%	10.93%
Total borrowers	28%	28%	29%	30%
Filings per borrower	2.71%	3.04%	2.82%	2.81%
DTI of defaulters	299%	296%	298%	304%
Filing too late			0.04%	0.05%
Overborrowing			7.14%	7.59%
Welfare gain from cross-subsidization				0.054%

Note: The table reports the weighted average of college and non-college behavioral consumers.

income.

However, over-optimistic beliefs have a sizeable effect on debt (compare columns (2) and (3)): the debt-to-earnings ratio rises from 6.6% to 7.5%. A key driver of this higher debt level is overborrowing, i.e. due to financial mistakes. Over-optimistic households overborrow by more than 7% in economy (3).[43] The impact on the frequency of bankruptcy filings is negligible. This effect partially stems from over-optimists overestimating their future ability to pay and filing too late. If suddenly made aware, an additional 0.04% would file for bankruptcy.

The pattern of filing too late induced by over-optimistic beliefs about one's future ability to repay introduces a form of commitment to repay. Filing too late means that behavioral agents roll over their debts for some levels of debt at which their informed selves (cf. column (2)) would choose to default. This results in *lower* average interest rates (compare columns (3) and (2)) due to two effects: First, there are slightly more borrowers when beliefs are over-optimistic (0.29 vs. 0.28) and

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

outstanding debt increases substantially. Second, despite more households borrowing larger sums, there are *fewer defaults per borrower* and lenders expect to recover *more* of the outstanding loans when borrowers are over-optimistic, which *decreases* average interest rates.

Column (4) in Table 4 reports the outcomes of behavioral agents in our benchmark economy. Thus, comparing it to column (3) identifies the effect of cross-subsidized interest rates.[44] Conditional on their type score, behavioral borrowers are pooled with rational borrowers, and thus face lower than actuarially fair interest rates. The cross-subsidization adds another 0.2pp to the debt-to-earnings ratio. The total number of borrowers also slightly increases.

Cross-subsidization has a counter-intuitive impact on the average borrowing rates of over-optimistic households: their average interest rates are slightly *higher* when pooled with rational households (10.93% versus 10.89%). This result arises due to the subtle impacts of cross-subsidization on the probability of default and banks' expected recovery given default. Facing cross-subsidized interest rate schedules changes the distribution of debt holdings, as low debts are cheaper to repay if rolled over. At the same time, large debts can be rolled over and continue to accumulate for longer before a borrower declares bankruptcy. Thus, borrowers file for bankruptcy with more debt. The debt-to-earnings ratio of defaulters increases by about 2%, from 298% (without pooling, column (3)) to 304% (with pooling, column (4)). Consequently, banks' recovery rate from defaulters declines, which leads to a slight increase in the average interest rate.

5.3 Removing Behavioral Bias: Full Information Economy

To assess the importance of information frictions on credit market aggregates and consumer welfare, we build on the analysis in Section 5.2 and compare the benchmark economy to a full information economy. In the full information environment, behavioral consumers are aware of their true income process and no longer make mistakes (see Table 5).[45] Lenders can identify the type of a borrower and hence condition their pricing of credit risk on whether a borrower is rational or behav-

[44]Behaviorals in the benchmark constitute 25% of the population vs. 100% in column (3).

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

Table 5: The Full Information Economy

	Non-College		College	
	Benchmark	Full Information	Benchmark	Full Information
Debt-to-income				
Rational	6.41%	6.59%	5.98%	6.16%
Behavioral	7.78%	6.84%	7.62%	6.04%
Average	6.83%	6.67%	6.22%	6.14%
Bankruptcy filings				
Rational	0.78%	0.78%	0.12%	0.13%
Behavioral	0.91%	0.88%	0.16%	0.15%
Average	0.82%	0.81%	0.13%	0.14%
Average interest rates				
Rational	11.70%	11.59%	8.71%	8.76%
Behavioral	11.82%	12.13%	8.77%	8.79%
Average	11.74%	11.76%	8.72%	8.76%
Paternalistic Welfare				
Rational		0.034%		0.008%
Behavioral		-0.055%		-0.018%
Average		0.006%		0.004%

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

ioral. As a result, there are no spillovers across types.

Compared to our benchmark, moving to the full information economy has a modest impact on debt, filings, and interest rates. That modest aggregate effect conceals sizable (but opposing) effects on the two types of consumer: as cross-subsidization ends, rational consumers borrow more, which partially offsets the decline in borrowing by behavioral consumers. This holds true within each education group. Furthermore, behavioral consumers account only for 25% of the population. Although their bankruptcy filings fall considerably under full information, this translates into a much smaller effect on education-specific averages.

Welfare is higher for rational agents and lower for behavioral agents in the full information economy compared to our benchmark.[46] This finding is not surpris-

[46] We adopt a paternalistic welfare measure (see Section 2.4). Perceived welfare is not a suitable

ing for the rational consumers. Although identifying behavioral agents does not change a realist's perception of herself, under full information, lenders can identify rational borrowers. This means rational borrowers no longer cross-subsidize behavioral borrowers and they are quoted lower interest rate *schedules*. Rational agents react by borrowing slightly more, which leads to slightly higher *average realized* interest rates in equilibrium. Overall, the full information economy leaves non-college (college) educated realists with a small increase in welfare of 0.034% (0.008%) consumption equivalence units.

Behavioral agents see a welfare loss. Behaviorals gain from being informed about their true income process as avoiding mistakes improves welfare. However, they lose the cross-subsidization that the rationals no longer pay. In our calibrated economy, the loss of the cross-subsidization dominates the gain from eliminating financial mistakes and leads to overall welfare losses of 0.055% and 0.018% for non-college and college educated behaviorals. The losses for the behavioral are larger than the gains for the rational, which is partly due to their smaller population share, since cross-subsidization per capita is greater for behaviorals.[47]

The comparison of our benchmark to the full information economy shows that the presence of behavioral consumers who cannot be directly identified by lenders lowers welfare for rational consumers, while behavioral consumers benefit from cross-subsidization. In line with our theoretical results in Section 3, this suggests that there is potential scope for regulatory policy targeted at reducing mistakes by behavioral borrowers to improve welfare. However, the impact on cross-subsidization is likely to impact who wins and loses. We turn to this question in Section 6.

5.4 Discussion

Our benchmark results offer several novel insights to the literature. Our work illustrates that cases where lenders are more informed than borrowers need not lead to predatory lending. We adopt the Bond, Musto, and Yilmaz (2009) definition that a "predatory loan" is *one that a borrower would decline if they had the same information*

measure since, due to over-optimism, the full information economy sees a reduction in the perceived welfare of behavioral agents due to their being fully informed of their true income process.

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

as the lender. Over-optimists are more likely than realists to consider themselves unlucky. While they agree with the estimation of their type score, they do not believe it conveys additional information. However, if made aware, behavioral agents would recognize that their borrowing is subsidized by rationals with the same type score. Hence, they would be happy to continue to borrow at this rate.

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

The benchmark calibration allows us to quantify the credit market spillovers across types (cf. Section 3.3). We find them to be quantitatively modest —– the welfare loss for rational borrowers in an economy where 25% of the population is behavioral, relative to an economy without behavioral consumers, is 0.02%. This loss combines both the effect of cross-subsidization and the indirect effects from the changes in interest rates that follow a downgrade in the type score after a negative income shock. The modest quantitative impact of the spillovers may be due to over-optimism applying only to the transitory income shocks. The insights in Athreya, Tam, and Young (2009) suggest that extending the analysis to include over-optimism over the persistent income process could result in larger spillovers.

6 Consumer Protection Policies

Proponents of credit market regulation often argue it can improve the outcomes of consumers who do not behave rationally or have limited financial literacy.[48] The slight increase in average welfare between our benchmark and the full information economy suggests there is potential scope for regulatory policy to intervene and

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

improve welfare. This leads us to investigate several policies that could alleviate the mistakes of behavioral borrowers who borrow too much and file too late. Our first experiments compare the effectiveness of small- versus large-scale financial literacy interventions (cf. Table 6). Next, we analyze two policies aimed at limiting borrowing—a tax on borrowing and borrowing limits—as well as a policy that makes filing for bankruptcy easier. Since, conditional on type score, over-optimists are indistinguishable from realists, these policies apply to everyone.[49] The results of these experiments are summarized in Table 7. In Appendix B.2 we show that our policy assessments remain similar as one varies the fraction of behavioral consumers or the degree of over-optimism.

6.1 Financial Literacy Education: A Challenge of Scaling

A natural policy to combat financial mistakes is financial literacy education. By educating over-optimists of their true income risk, education should reduce financial mistakes. Moreover, by directly targeting behavioral consumers, a financial literacy program would not directly impact the borrowing options for rational consumers. To formalize this intuition, we evaluate the best case for financial literacy education. We assume that it is perfectly targeted at behavioral consumers and makes them fully internalize their true income risks. This hypothetical education campaign can be seen as the upper bound of what financial literacy education can achieve.[50]

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

This intervention generates a welfare gain of 0.032% and 0.009% for a newborn over-optimist with and without college education, respectively (see the first

[49]Type-score dependent policies are considered in Section 7.

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

Table 6: Welfare Effects of Financial Literacy Education: Small Scale vs GE

	small scale	full GE
Rational, Non-college	0	0.034%
Rational, College	0	0.008%
Rational total	0	0.022%
Behavioral, Non-college	0.009%	-0.055%
Behavioral, College	0.032%	-0.018%
Behavioral total	0.014%	-0.046%
Non-college, total	0.003%	0.006%
College, total	0.005%	0.004%
Aggregate	0.004%	0.005%

column in Table 6). These gains reflect a change in the sequence of life-time borrower decisions, as financial literacy leads to a borrower no longer overborrowing or filing too late.[51] At the same time, the behavioral borrower retains cross-subsidization. The reason that an over-optimist with a college degree sees roughly three times the welfare gains of a non-college household is that the college educated borrow larger amounts over the first part of their lives. This is driven by the steeper life-cycle earnings profile of college graduates which plays a larger role in motivating their borrowing than it does for non-college.

The benefits of a small-scale financial literacy intervention in our model appear broadly consistent with empirical findings of positive impacts on consumer behavior after financial literacy programs.[52] In general, these studies have employed modest population sizes and are thus similar in spirit to our exercise.

We next use our model to examine the impact of extending the financial literacy program to inform all newborn over-optimists of their true income risk. This thought experiment corresponds to our full information economy in Section 5.3, where all consumers are aware of their true income risk. While over-optimists no longer make mistakes, lenders price credit separately for both borrowers types. This change in lender behavior means that over-optimist borrowing is no longer cross-subsidized by rationals, which flips the effect for over-optimists to a *wel-*

[51]The one period gains (taking all past wrongly informed decisions as given) are tiny.

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

fare loss of 0.055% and 0.018%, respectively, for non-college and college. A non-college over-optimist loses more when cross-subsidization ends because borrowing to smooth against transitory income shocks is a relatively more important force than it is for the college educated. Combined with the calibration of the default costs which results in non-college borrowers being more likely to file, this results in non-college borrowing becoming more expensive under separate pricing. For rationals, the elimination of cross-subsidization results in a welfare gain of 0.022%, despite their not being directly impacted by the program. The gain is four times as large for the non-college rationals compared to college. This asymmetry is the flip side of the welfare loss of behavioral borrowers, since cross-subsidization is a transfer from rational to behavioral borrowers within each education group.

The welfare loss for over-optimists when scaling up financial literacy education highlights the importance of taking into account lender's response to such programs. By adjusting their interest rate schedules, lenders more accurately price in the underlying default risk of over-optimists. In our environment, this updated pricing of credit risk more than offsets the welfare gains from avoiding mistakes. Our equilibrium model of unsecured credit and risk-based pricing thus suggests that the welfare gains found in small-scale financial literacy experiments cannot easily be scaled to the entire population.

6.2 Higher Borrowing Costs

A central argument for regulating consumer credit is to preempt overborrowing. This motivates policies aimed at reducing the incentive to (over) borrow, ranging from limiting the roll-over of short-term loans, restricting the amount of simultaneous loans, introducing cool-off periods, increasing underwriting requirements, and introducing centralized loan databases. By increasing a lender's costs, many of these regulations result in higher lending costs.[53] If individuals overborrow, a higher cost of lending may be beneficial if it discourages "mistaken" borrowing. On the other hand, there is a deadweight cost attached to a higher cost of lending. Moreover, a higher borrowing cost affects everyone, including rational people who use credit correctly.

[53]The welfare implications of an increase in the transaction cost likely differ from a tax on lending as there is no additional revenue (net of administration costs) to be rebated to consumers.

Table 7: Policy Experiments

Parameter	(1) Bench	(2) Borrow Cost ↑ $\tau = 7.9\%$	(3) Default Cost ↓ $\gamma = 50\%$	(4) Debt-to-income $\leq 100\%$	(5) Debt-to-income $\leq 100\%$ if $s < 0.65$
Debt-to-income					
Rational, non-college	6.41%	5.46%	4.72%	5.74%	6.07%
Behavioral, non-college	7.78%	6.67%	5.77%	6.94%	7.29%
Rational, college	5.98%	4.68%	4.35%	3.99%	5.97%
Behavioral, college	7.62%	6.04%	5.45%	5.11%	7.61%
Bankruptcy filings					
Rational, non-college	0.78%	0.78%	1.89%	0.76%	0.77%
Behavioral, non-college	0.91%	0.90%	2.16%	0.88%	0.89%
Rational,college	0.12%	0.12%	0.46%	0.13%	0.13%
Behavioral, college	0.16%	0.15%	0.57%	0.16%	0.16%
Average interest rates					
Rational, non-college	11.70%	12.86%	22.39%	11.28%	11.53%
Behavioral, non-college	11.82%	12.99%	23.42%	11.36%	11.61%
Rational, college	8.71%	9.71%	10.87%	8.59%	8.71%
Behavioral, college	8.77%	9.76%	11.40%	8.58%	8.77%
Paternalistic Welfare					
Rational, non-college		-0.19%	0.64%	-0.07%	-0.03%
Behavioral, non-college		-0.20%	0.66%	-0.09%	-0.05%
Rational, college		-0.22%	0.23%	-0.25%	0.00%
Behavioral, college		-0.22%	0.25%	-0.26%	0.00%
Financial Mistakes					
Filing too late, non-college	0.04%	0.14%	0.01%	0.01%	0.02%
Filing too late, college	0.08%	0.05%	0.14%	0.01%	0.09%
Overborrowing, non-college	6.66%	8.54%	6.21%	6.44%	6.10%
Overborrowing, college	9.78%	9.31%	10.46%	8.64%	9.82%

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

Our borrowing cost experiment increases the transaction cost of lending by one percentage point, from 6.9% in the benchmark to 7.9%, so that the new risk-free lending rate is 8.9%. Higher borrowing costs reduce borrowing by both non-college and college educated consumers (see column (2) in Table 7). Bankruptcy filings remain almost constant, although filings by behavioral consumers decline slightly. If a policymaker's objective were to reduce debt, then this policy could be considered a success.[54] However, the policy increases our measure of filing too late more than threefold for the non-college and over-borrowing also increases. The opposite is observed for college graduates, who make fewer mistakes with a higher borrowing cost. These opposing effects on financial mistakes directly follow from the discussion at the end of Section 5.1. Even with higher borrowing cost, the non-college group continues to borrow to smooth bad transitory shocks. Behaviorals continue to borrow and default less than in the benchmark, even though they should default more in the face of higher borrowing cost. In contrast, college graduates mainly borrow to smooth consumption over the life cycle and reduce their borrowing in response to higher borrowing cost, lowering their mistakes.

Although the behavioral college educated make fewer mistakes, a higher cost of borrowing lowers their welfare as well as the welfare of rational consumers. Higher borrowing rates tighten the endogenous borrowing limits and hinder consumers' ability to borrow to smooth. As a result, even though mistakes by behavioral (college educated) consumers are reduced, this policy leaves both types of consumers with lower welfare.

Higher borrowing costs have a similar impact on behavioural and rational consumers' borrowing and bankruptcy filings. As a result, a change in borrowing costs does not significantly change cross-subsidization and hence the welfare effects are similar for both types. When varying default costs and debt-to-income limits, we also find similar effects on behavioral and rational consumers. In Section 7 we explore whether policies that condition on type-scores to better target behavioural borrowers can be effective.

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

6.3 Lower Cost of Default

To target defaulting too late, we consider a policy that makes default easier. The simplest way to implement this in our model is to lower the default cost. Column (3) in Table 7 reports the results of reducing the required repayment, γ, from 82% in the benchmark to 50% of income above the exemption level. This reduction in default costs substantially increases the default rate of all types of consumers. Due to higher average income, college educated defaulters pay a higher default cost in benchmark. Thus, lowering these costs nearly quadruples filings of college graduates. In absolute terms, filings increase the most for non-college graduates, with an increase of more than 1 percentage point. Within each education group, the increase is larger for over-optimists. Facing higher default rates, lenders increase their interest rate schedules, which tightens the endogenous borrowing constraints. As a result, average borrowing interest rates jump to nearly 23% for non-college and 11% for college. Consequently, households reduce their borrowing. These direct and indirect effects of reduced default costs impact financial mistakes in opposite directions for the two education groups. Mistakes are reduced for the non-college educated, but increased substantially for college graduates. This is the opposite of the effects of higher borrowing cost (cf. Section 6.2), because borrowing in response to temporary negative shocks—which is more common for non-college borrowers —becomes less attractive vis-à-vis defaulting. Thus, non-college mistakes decrease. On the other hand, behavioral college graduates trying to smooth consumption over the life cycle at significantly higher interest rates should default much more and borrow much less. Behavioral college graduates adapt too little. Consequently, college mistakes increase.

Lowering the cost of default increases welfare for both education groups. As non-college educated borrowers have a weaker motive to smooth income over the life-cycle, the cost of paying higher interest rates is lower for them and they benefit relatively more. However, since rational consumers also benefit, these gains are not driven by changes in mistakes by behavioral borrowers. Instead, our calibration yields overall default costs that are higher than the welfare maximizing level. Thus, these gains reflect the well documented feature that a more lenient bankruptcy system can improve welfare, as it increases insurance against adverse shocks (see Livshits, MacGee, and Tertilt (2007) and Exler and Tertilt (2020)).

6.4 Debt-to-Income Limits

A direct way of limiting consumer debt levels is to cap a borrower's debt relative to their income (DTI).[55] Besides formal limits in some markets, these policies are also consistent with the spirit of the Truth in Lending Act, which requires lenders to evaluate borrowers' ability to repay by taking their income into account.[56]

To implement DTI limits in the model, we focus on current persistent income hz. We abstract from transitory shocks, as they contain no information about future income realizations when the debt becomes due. Furthermore, lenders may have little information on contemporaneous temporary income shocks in practice. The debt-to-income ratio relates current borrowing to income: $q(\cdot)d'/(hz)$.[57]

We report the effects of a relatively loose debt-to-income limit of 100% in column (4) of Table 7. Despite being relatively lax, it prohibits large loans, which reduces debt by 0.7 to 2 percentage points, depending on the type. The decline is larger among college graduates and – within education groups – larger for the over-optimists. Smaller outstanding debts lead to fewer bankruptcies for the non-college graduates. Fewer bankruptcies lead to lower-risk premia and drive down average borrowing interest rates. Average interest rates are reduced by roughly half a percentage point for non-college graduates under the debt-to-income limit. The effect is much smaller for college graduates, mainly because bankruptcy filings *increase* slightly. As college educated borrowers have a steeper life-cycle earnings profile, a larger share of their borrowing occurs when they are younger. The interaction between higher future earnings due to the steep life-cycle profile and the calibrated bankruptcy costs means that the default risk is relatively low. However, the DTI limit of 100% limits more highly leveraged borrowers in their ability to respond to adverse shocks and thus drives bankruptcy filings *up* slightly. This counteracts the overall lower amount of debt and dampens the impact on interest

[55] We discuss an alternative limit on debt service relative to income in a previous version of this paper, cf. Exler et al. (2021), Appendix D.

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

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

rates.

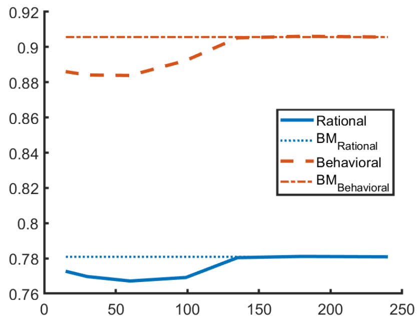
Introducing the debt-to-income limit significantly reduces financial mistakes. Late filing is nearly eliminated (0.01%) and overborrowing drops by almost a percentage point for college graduates, and by a smaller amount for non-college graduates. Despite these positive effects, the total welfare effects are negative (especially for college graduates) as the cost of constraining consumers' borrowing decisions exceeds the benefit of reducing financial mistakes: Depending on their type, consumers lose between 0.07 and 0.26% in consumption equivalence units when debt is capped at current income.

7 Score-Dependent Consumer Protection Policies

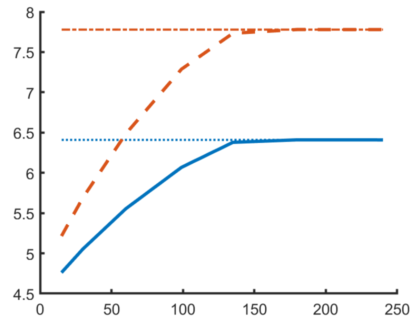
Introducing borrowing limits for all agents can reduce financial mistakes but lowers consumers' welfare. Could a policy that focuses these interventions on consumers who make mistakes be welfare improving? Since policymakers cannot directly observe which consumers are behavioral, we examine the effectiveness of using type scores as a proxy. Borrowers with a low type score are more likely to be behavioral. Thus, a policy that applies only to low type scores should reduce financial mistakes with lessened adverse welfare effects as consumers with high type scores, who are likely rational, would not be directly impacted. In addition, college educated consumers were most adversely affected by a borrowing limit. Since the fraction of college graduates who are behavioral is less than in the non-college population, college borrowers have higher average scores and thus are less likely to be restricted by a score dependent policy.

We analyze the effect of debt-to-income limits that apply only to consumers below a given type-score threshold along two dimensions: varying the debt-to-income limit and varying the threshold score (see Appendix C for further details).[58] Policies that apply to scores (strictly) below 0.45 affect almost no one (less than 1%), while a type score of 0.9 would affect nearly the entire population (see Table A6 in the Appendix.). However, although 25% of the population are behavioral, their share of the population with low type scores is higher as they comprise 32%

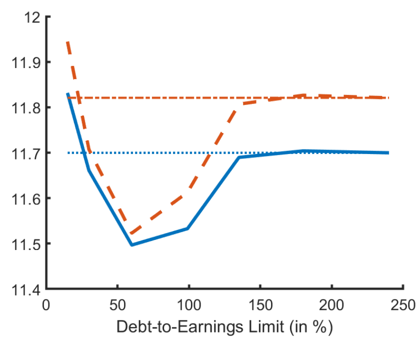
[58]Policies targeting households above/below a threshold are common. See Mitman (2016) for an analysis of the 2009 Home Affordable Refinance Program, which effectively subsidized borrowers with loan-to-value ratios between 80 and 125%.



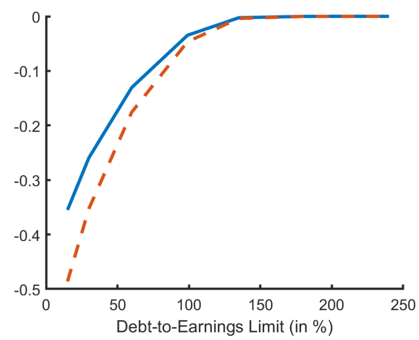
(a) Bankruptcies (in %)



(b) Debt to income (in %)



(c) Interest Rates (in %)



(d) Welfare (in % CEV)

Figure 3: Debt-to-Income Limits Below Type Score 0.65, non-college educated

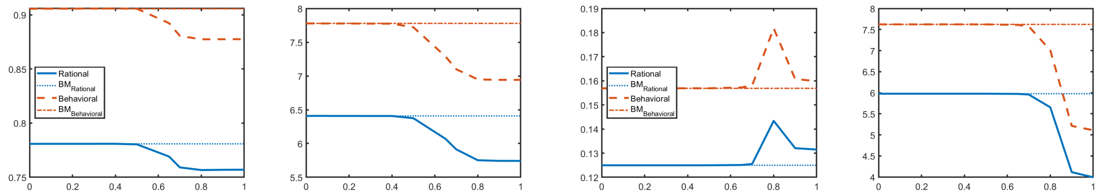
of those with scores at or below 0.75, and a majority of those with scores at or below 0.45. When targeting behavioral agents, policymakers thus face a trade-off between precision and coverage. On the one hand, lower thresholds affect fewer rational agents inadvertently at the cost of not including some behavioral agents. On the other hand, higher thresholds capture a larger share of behavioral borrowers but also capture more rational agents.

To examine the impact of varying the debt-to-income limit, we fix the type-score threshold at 0.65. In equilibrium, 22 percent of the population have a type score strictly below 0.65 and are subject to the policy. While less than one percent of college graduates is affected, approximately 32 percent of rational non-college and 42 percent of behavioral non-college are subject to the policy. Although behavioral borrowers have lower type scores on average, roughly two-thirds of those affected are rational agents. Table 7 column (5) displays the effects of the 100% DTI limit considered in Section 6.4 when only binding for consumers with a type score below 0.65. This policy has essentially no effect on college graduates since hardly any college graduates have a type score below 0.65. For the non-college, the effect is similar to the untargeted debt-to-income limit policy, although the score-dependent policy has a smaller negative impact on welfare.

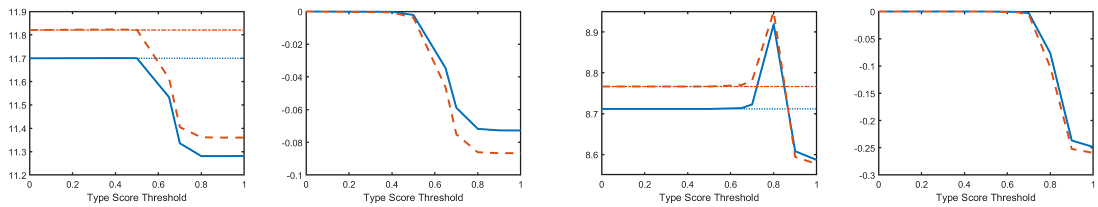
The effects on non-college bankruptcies, debt, interest rates, and welfare are shown in Figure 3 for debt-to-income limits ranging from 15% to 240% of annual income (college graduates are not significantly affected by the policy, see Table 7). Not surprisingly, the lower the debt-to-income limit, the lower the average debt (see panel (b)). Once the limit reaches about 140%, it ceases to bind and debt returns to its benchmark level. This is a large number, given that the average debt-to-income ratio for non-college graduates is only 6.8%.

Do more binding debt-to-income limits also lower filing rates? Initially yes, see panel (a). This is consistent with the effect advocates for regulation have in mind when arguing that preventing people from "borrowing too much" will reduce bankruptcies. However, very tight DTI limits cause filings to increase. Tight limits prevent borrowing by households that are good credit risks but experience temporary bad luck (e.g., an expense shock). Moreover, for large shocks, some households that could have borrowed (and repaid) without declaring bankruptcy are unable to borrow enough with tight DTI limits and declare bankruptcy. Consequently, bankruptcy filing rates and interest rates are u-shaped in the DTI limit. The tighter the limit, the more low-risk consumers stop borrowing so as to preserve their capacity to smooth future adverse shocks by accumulating savings, while the higher-risk, but desperate, continue to borrow. This selection effect sees tight DTIs drive average interest rates above the benchmark level (see Figure 3 panel (c)).

From a welfare perspective, stricter debt-to-income limits are not good policy, even in the range where filings decrease, as average welfare declines (see Figure 3 panel (d)). These welfare effects reflect the costs of limiting access to credit to smooth shocks to income, and the welfare declines are larger for behavioral than for rational households. The larger adverse impact on behavioral borrowers from tight borrowing limits is twofold: since they are more likely to experience negative transitory income shocks, they are more likely to have lower type scores and be borrowing constrained. Additionally, more negative shocks increase the need to borrow for consumption smoothing. Even though this policy lowers debt and bankruptcies, it also lowers consumers' welfare.



(a) Bankruptcy, N (b) Debt/Income, N (e) Bankruptcy, C (f) Debt/Income, C



(c) Avg Interest, N (d) CEV, N (g) Avg Interest, C (h) CEV, C

Figure 4: Debt-to-Income Limit of 100% for Different Type-Score Thresholds

These negative welfare effects may not hold for alternative type-score thresholds. We now fix the debt-to-income limit at 100% and vary the type-score threshold from 0 to 1 (see Figure 4 which now includes results for college graduates). For low thresholds, the policy applies to hardly anyone, explaining the lines that are almost flat until about 0.5 for non-college graduates and 0.7 for college graduates. Once the debt limit becomes binding for a sizeable fraction of people, average debt begins to fall. The decline starts much earlier for non-college compared to college graduates. This is not surprising, since a larger fraction of the non-college population is affected at lower scores. For example, as Table A6 shows, a score of 0.6 affects more than 15% of the non-college population, but hardly any college graduates. As debt declines, bankruptcies for non-college graduates also decline. Bankruptcies for college graduates, on the other hand, increase, which may seem counter-intuitive. The reason for these differential effects is that borrowing to smooth consumption over the life-cycle is a more important driver of borrowing for college than non-college consumers, while transitory income shocks drive a larger share of non-college borrowing. Around the type score threshold of 0.8, young college graduates with high debts and type scores close to the college prior are affected by the DTI limit, reducing their ability to borrow and thus causing them to default.

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

8 Assessing the Case for Consumer Credit Regulation

Our theoretical analysis shows that there is scope for (paternalistic) welfare-improving policies when the costs of financial mistakes by households are sufficiently large. In our quantitative analysis, we find that several commonly discussed consumer protection regulations do not improve welfare despite behavioral consumers over-borrowing. However, alternative assumptions around the nature of behavioural biases, a richer set of lending contracts or the nature of competition could strengthen the case for consumer protection regulations. In this section, we briefly discuss how these features could impact our results in the context of selected papers from the literature. While these forces could strengthen the case for the consumer protection regulations we examine, their quantitative impact is unclear. Given the role we find for default in shaping the pattern of cross-subsidization and the welfare evaluation of regulations, this suggests that further research which integrates default in equilibrium with these features is needed.

While over-optimism leads to over-borrowing in our model, much of the related behavioral literature that explores the case for regulating consumer credit markets has focused on some form of hyperbolic discounting (e.g. Laibson, Tobacman, and Repetto (2000), Ericson and Laibson (2019), Nakajima (2012), Nakajima (2017)). Sophisticated hyperbolic discounters value commitment for their future selves and consequently might prefer tighter borrowing limits or lower default cost.[59] Gottlieb and Zhang (2021) find that long-term contracting can alleviate wel-

[59] Lower default costs *reduce* the amount of debt sustainable in equilibrium and thus lead to tighter borrowing constraints.

fare losses from present bias. They also find that the length of the contracting horizon, bargaining power of consumers and the non-exclusivity of contracts can impact the distortions associated with present bias.

Perhaps more interesting than the nature of behavioral bias per se is whether behavioural biases could be exploited by sophisticated lenders tailoring features of debt contracts.[60] This idea has been formalized in Heidhues and Kőszegi (2010), who showed that lenders can exploit consumers with self-control problems by backloading payments via large penalties for delaying repayment. Ru and Schoar (2020) examine the contractual details of a sample of credit card offers, and find evidence that suggests that credit companies are more likely to offer contract structures with more back-loaded fees to customers with lower levels of education. Adams, Bord, and Katcher (2022) however, document that even for those who borrow regularly on credit cards ("heavy revolvers") late fees account for a modest share of total financing costs, averaging roughly 3 dollars per month versus over 60 dollars in interest charges.[61]

Central to our paper is a force that attenuates the extent to which lenders can use backloaded fees to exploit naive consumers: the option to default. In model environments without default (like that of Heidhues and Koszegi), naive consumers who overborrow and delay repayment pay large penalties. In our model, over-optimists also over-borrow, but default more often than rational borrowers. Default generally acts in the opposite way to a penalty as it redistributes resources from lenders to the defaulting borrower. The default option impacts the quantitative scope for backloading contracts in two ways. First, higher future payments can make default more likely. Second, since over-optimistic agents are worse credit risks, default combined with the pooling of behavioral and rational borrowers results in cross-subsidization (cf. Section 3). As we show, the welfare implications of policies that aim to reduce overborrowing by over-optimists can be influenced by how they impact cross-subsidization across types.[62]

[60]In our model, lenders cannot offer contracts which would be chosen by over-optimists and not rational borrowers. Although this assumption plays a key role in the tractability of our type scoring model, this would not necessarily be the case of alternative specifications of behavioural bias.

[61]This suggests that back loaded late fees are quantitatively much less important than the more visible interest charges. However, if backloaded fees reversed the flow of cross-subsidization in our model, the case for regulation would be strengthened: behavioral consumers would avoid financial mistakes and exploitation.

[62]This pattern of cross-subsidization is the opposite of that documented in markets such as life-

Our framework also features a second force which limits exploitative contracts: borrowers can switch lenders. Most unsecured revolving credit products such as credit cards do not impose a fee if a borrower pays off the balance on one account whilst borrowing on another account. This effectively makes it possible to switch lenders, even without a balance transfer, and motivates our abstracting from lenders enforcing long-term contracts with fixed interest rates.[63]

There are a number of reasons for regulating consumer credit markets that are beyond the scope of our current model environment. Independent of financial mistakes and cross-subsidization, Galenianos and Gavazza (2022) and Raveendranathan, Stefanidis, and Sablet (2023) show that well-designed credit market regulations can be beneficial when lenders possess market power.[64] There is also evidence that borrowers not only get their future income wrong: Ameriks et al. (2023) explore the effects of cognitive decline in financial decision making. Bertrand and Morse (2011) examine whether well-designed disclosure of the cost of credit lowers the amount borrowed. The U.S. Government Accountability Office (2006) also highlights the need for disclosure regulation as lenders design contracts that are difficult to understand and cardholders regularly fail to understand key aspects. On the other hand, Allcott et al. (2022) find limited evidence of present bias in borrowers in the payday lending market, a market that is usually viewed as attracting mainly behavioral borrowers.[65]

9 Conclusion

In this paper, we quantitatively analyze consumer credit markets with behavioral consumers and default. Incorporating over-optimistic borrowers into a standard incomplete-markets economy with unsecured debt and equilibrium default pro-

insurance (e.g., Gottlieb and Smetters (2021)) where consumers default by ceasing to pay means that they are not eligible for future insurance payouts. In this case, cross-subsidization takes the form of lapsers (who default on their premia) paying a higher than actuarily fair price which benefits those who remain in good standing.

[63]Calem and Mester (1995) and Calem, Gordy, and Mester (2006) document some switching cost in the credit card market in the form of information frictions or time cost. However, most consumers have multiple credit cards and switching lenders is relatively common.

[64]Bethune, Saldain, and Young (2023) show that interest rates caps on payday lending can be welfare improving if some borrowers are not aware of lower interest rates offered by other lenders.

[65]Similar to our finding, Allcott et al. (2022) conclude that further restricting access to payday lending would not improve borrower welfare.

vides several interesting insights. First, by modelling behavioral consumers as over-optimistic and unaware, we develop a tractable theory of type scoring. Second, our work shows that spillovers in credit markets arise in equilibrium between rational and behavioral borrowers. In a world where lenders can only imperfectly infer a borrower's type, partial pooling of rational and behavioral borrowers is likely to ensue. Since the behavioral borrowers in our model are at higher risk of default, in equilibrium they are cross-subsidized by rational borrowers.

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

This paper points to several promising avenues for future research.[66] First, we show that many consumer protection policies can adversely affect borrowers even when targeted at financial mistakes. Further work should ask whether more nuanced policies could improve welfare. Second, we show that transitory shocks can have lasting effects on the terms of credit as they can affect borrowers' type scores and thereby their current and future interest rate schedules. This can make consumption smoothing harder when credit is needed most. This mechanism deserves further analysis. Third, type scores summarize the information lenders collect about a borrower's type. The speed of learning determines the amount of pooling over the life-cycle. Estimating the amount of pooling by age empirically could offer insights into the speed of learning. Finally, our framework in which screen-

[66]More work on the robustness of whether bankruptcy costs are too low or too high would also be useful. Nakajima (2017) in a model with hyperbolic discounters that allows for default finds that over-borrowing can be reduced by increasing the cost of default. The reason is that a high cost of default increases commitment, which is lacking in consumers with self-control problems. Similarly, Nakajima (2012) show that tighter borrowing limits are welfare improving for this reason. However, neither of these papers features expense shocks which increase the insurance value of bankruptcy, and thus push towards lower default costs.

ing contracts are not feasible naturally leads to pooling. It may be useful in other contexts where over-optimism has been documented, such as health, longevity, and the ability to complete certain tasks. Thus, our core insights may be useful for understanding health insurance, life insurance, and employment contracts.

While there remain several forces that could strengthen the case for the consumer lending regulations we examine, our paper points to several key mechanisms that should be included in future quantitative work on this subject. The possibility of default and the option to switch borrowers can limit the quantitative scope for lenders to use exploitative contracts to charge higher than actuarially fair charges on behavioral borrowers. In addition, when limited information results in the partial pooling of rational and behavioral borrowers, cross-subsidization that results from default may result in cross-subsidization of behavioral borrowers. These forces have been (surprisingly) largely ignored in much of the literature examining whether behavioral consumers need protection from lenders. This points to the need for future quantitative research that incorporates the key mechanisms highlighted in our paper with those of work in the spirit of Heidhues and Kőszegi (2010) or Johnen (2020).

References

Adams, Robert, Vitaly Bord, and Bradley Katcher. 2022. "Credit Card Profitability." *FEDS Notes*, September.

Adams, Robert M., and Vitaly M. Bord. 2020, October. "The Effects of the COVID-19 Shutdown on the Consumer Credit Card Market: Revolvers versus Transactors." Technical Report, Board of Governors of the Federal Reserve System.

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

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

Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebel. 2018. "Do Banks Pass through Credit Expansions to Consumers Who want to Borrow?" *Quarterly Journal of Economics* 133 (February): 129–190.

Allcott, Hunt, Joshua Kim, Dmitry Taubinsky, and Jonathan Zinman. 2022. "Are High-Interest Loans Predatory? Theory and Evidence from Payday Lending." *Review of Economic Studies* 89:1041–1084.

Ameriks, John, Andrew Caplin, Minjoon Lee, Matthew Shapiro, and Christopher Tonetti. 2023. "Cognitive Decline, Limited Awareness, Imperfect Agency, and Financial Well-Being." *American Economic Journal: Insights* 5 (1): 125–140.

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

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

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

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

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

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

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

Bertrand, Marianne, and Adair Morse. 2011. "Information Disclosure, Cognitive Biases, and Payday Borrowing." *Journal of Finance* LXVI (3): 1865–1893.

Bethune, Zachary, Joaquin Saldain, and Eric Young. 2023, December. Consumer Credit Regulation and Lender Market Power. mimeo.

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

Calem, Paul S., Michael B. Gordy, and Loretta J. Mester. 2006. "Switching Costs and Adverse Selection in the Credit Card Market: New Evidence." *Journal of Banking and Finance* 30 (6): 1653–1685 (June).

Calem, Paul S., and Loretta J. Mester. 1995. "Consumer Behavior and the Stickiness of Credit Card Interest Rates." *American Economic Review* 85 (5): 1327–1336 (December).

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

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

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

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

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

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

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

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

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

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

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

Ericson, Keith, and David Laibson. 2019. "Intertemporal Choice." Chapter 1 of *Handbook of Behavioral Economics*, edited by Doug Bernheim and Stefano DellaVigna, Volume 2, 1–67. Elsevier.

Exler, Florian, Igor Livshits, James MacGee, and Michèle Tertilt. 2021, December. "Consumer Credit with Over-Optimistic Borrowers." Working paper WP 21-42, FRB of Philadelphia. `https://doi.org/10.21799/frbp.wp.2021.42`.

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

Galenianos, Manolis, and Alessandro Gavazza. 2022. "Regulatory Interventions in Consumer Financial Markets: The Case of Credit Cards." *Journal of European Economic Association* 20 (5): 1897–1932.

Gottlieb, Daniel, and Kent Smetters. 2021. "Lapse-Based Insurance." *American Economic Review* 111 (8): 2377–2416.

Gottlieb, Daniel, and Xingtan Zhang. 2021. "Long-Term Contracting With Time-Inconsistent Agents." *Econometrica* 89 (2): 793–824.

Gul, Faruk, and Wolfgang Pesendorfer. 2001. "Temptation and Self-Control." *Econometrica* 69 (6): 1403–1435.

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

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

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

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

Johnen, Johannes. 2020. "Dynamic Competition in Deceptive Markets." *Rand Journal of Economics* 51 (2): 375–401.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Mueller, Andreas I., and Johannes Spinnewijn. 2023. "Expectations data, labor market, and job search." In *Handbook of Economic Expectations*, edited by Rüdiger Bachmann, Giorgio Topa, and Wilbert van der Klaauw, 677–713. Academic Press.

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

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

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

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

Raveendranathan, Gajendran, Georgios Stefanidis, and Guillaume Sablet. 2023. "Rate Caps on Revolving Credit Lines: Who Benefits?" McMaster University mimeo.

Ru, Hong, and Antoinette Schoar. 2020. "Do Credit Card Companies Screen for Behavioural Biases?" *BIS Working Papers No. 842*, February.

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

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

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

U.S. Census. 2021. Educational Attainment of the Population 18 Years and Over, by Age, Sex, Race, and Hispanic Origin. `https://www2.census.gov/programs-surveys/demo/tables/educational-attainment/2021/cps-detailed-tables/table-1-1.xlsx`.

U.S. Government Accountability Office. 2006. Credit Cards: Increased Complexity in Rates and Fees Heightens Need for More Effective Disclosures to Consumers (GAO-06-929). `https://www.gao.gov/products/gao-06-929`.

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

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

Online Appendix

A Calibration

A.1 Over-optimism and Transitory Income Risk

To measure financial literacy and the relative frequency of low transitory income realizations, we use data from the 2016 and 2019 SCF. The 2016 wave added a set of questions on the financial literacy of households. We use the number of correct answers to three questions on the topics of risk diversification, interest rate compounding, and inflation (X7558 to X7560) as a measure of financial literacy. Table A1 shows that 85% of college educated respondents correctly answered 2 or 3 questions. Only 69% of high school educated respondents achieved the same. The number of correctly answered question is also highly positively correlated with income (see final column in Table A1).

As discussed in Section 4, we proxy behavioralism by low financial literacy. We designate repondents with at most one correct question as having low financial literacy. As presented in Table A1, this results in a share of $\lambda_N = 31\%$ behavioral amongst non-college households and a share of $\lambda_C = 15\%$ behavioral amongst college educated households.

The SCF contains a question (X7650) asking whether respondents' total income in the previous year was unusually low, normal, or unusually high compared to their expectation during a "normal" year. Table A1 reports that measure by education group and high vs. low financial literacy scores. For the non-college educated, we find that among those who answered at most 1 literacy question correctly, 22% experienced unusually low income, compared to 17% among households that answered two or three correctly. For college educated respondents, 18% of low financial literacy respondents see unusually low income compared to 14% amongst those with high financial literacy. We define the degree of over-optimism by the spread in downside income risk and calculate very similar values of $\psi_N = \text{Prob}_N^B(\eta_1)/\text{Prob}_N^R(\eta_1) = 22/17 = 1.28$ for non-college and $\psi_C = \text{Prob}_C^B(\eta_1)/\text{Prob}_C^R(\eta_1) = 18/14 = 1.29$ for college. As mentioned in Section 4, we choose $\psi = 1.285$ for both groups. We use the *ratio* of the probabilities of adverse shocks across borrowers (and not the levels) to map the single-year obser-

Table A1: Unusual income and financial literacy

# Correct questions	Share	Fraction with income unusually low	normal	high	Total Income
No college degree					
0 or 1	0.31	0.22	0.69	0.09	49,583
2 or 3	0.69	0.17	0.72	0.11	66,766
Ratio (0 or 1) / (2 or 3)		1.28	0.96	0.86	
With college degree					
0 or 1	0.15	0.18	0.74	0.08	72,271
2 or 3	0.85	0.14	0.76	0.10	157,450
Ratio (0 or 1) / (2 or 3)		1.29	0.98	0.78	

Note: Results for pooled SCF 2016 and 2019 for 25-55 years olds. With college degree are households that report at least a first college degree for the household head (x5931). Total income is the total received income of the household from all sources before taxes and deductions (x5729).

vations from the SCF into our triennial model.

Given the overall probabilities of the transitory shock Prob$(\eta) = [0.1, 0.8, 0.1]$, the degree of over-optimism $\psi = 1.285$ and the shares $\lambda_N = 31\%$ and $\lambda_S = 15\%$ uniquely determine the transitory income probabilities for both, rational and behavioral, agents in the two education groups. To see how, note that by definition $\text{Prob}_e(\eta_1) = (1 - \lambda_e)\text{Prob}_e^R(\eta_1) + \lambda_e \text{Prob}_e^B(\eta_1)$. Given the definition of ψ, this is $\text{Prob}_e(\eta_1) = (1 - \lambda_e)\text{Prob}_e^R(\eta_1) + \lambda_e \psi \text{Prob}_e^R(\eta_1)$. Hence, $\text{Prob}_e^R(\eta_1) = \text{Prob}_e(\eta_1)(1 - \lambda_e + \lambda_e\psi)^{-1}$ and $\text{Prob}_e^B(\eta_1) = \text{Prob}_e(\eta_1) \times \psi/(1 - \lambda_e + \lambda_e\psi)$ for both education groups $e \in \{N, C\}$. Finally, $\text{Prob}_e^T(\eta_3) = 1 - \text{Prob}_e^T(\eta_2) - \text{Prob}_e^T(\eta_1)$ for $T \in \{B, R\}$ and $e \in \{N, C\}$. See Table 1 for the resulting values.

A.2 Life-Cycle Dynamics of Income

To construct the life-cycle component h_j in Equation 3, we calculate a vector of earning multipliers consistent with the estimates in Hubbard, Skinner, and Zeldes (1994). The authors estimate a third degree polynomial in age to represent average life-cycle effects. The resulting multipliers, normalizing aggregate economy-wide income to one, are depicted in Figure A1.

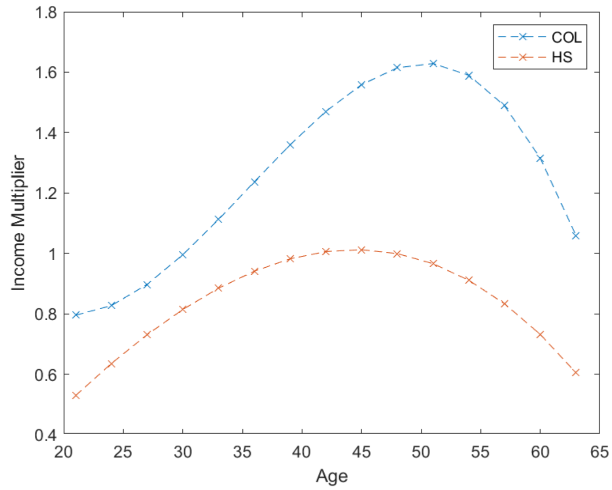


Figure A1: Life-Cycle Earning Multipliers

B Robustness

Our calibration strategy yields an estimate of the fraction of behavioral consumers and their degree of over-optimism. Yet, given the limited data and lack of consensus in the literature we view it as a suggestive rather than a definitive estimate. In Appendix B.1, we investigate the effect of changing the fraction of behavioral consumers, λ, and the degree of over-optimism, ψ. When comparing economies with different λ or ψ, we hold fixed all other parameters.[67] In Appendix B.2, we assess the robustness of Section 6's policy experiments with respect to λ and ψ.

B.1 Varying Over-optimism

Table A2 reports aggregate and type-specific outcomes as the fraction of behaviorals in the economy is varied from zero to one. As the fraction of behavioral borrowers rises, both average debt-to-income and default rise while average borrowing interest rates remain roughly constant. These aggregates are driven by changes in the composition of borrowers and changes in individual behavior. The overall higher debt-to-income ratios and default rates of behavioral consumers directly account for the rise in average debt-to-income and bankruptcy filings as λ

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

Table A2: Varying the Fraction of Behavioral Agents

	Fraction of behavioral borrowers λ				
	0	0.12	0.25[†]	0.5	1
Debt-to-income					
Rational	6.39%	6.29%	6.18%	6.05%	
Behavioral		7.85%	7.73%	7.58%	7.43%
Average	6.39%	6.47%	6.54%	6.76%	7.43%
Bankruptcy filings					
Rational	0.54%	0.52%	0.50%	0.43%	
Behavioral		0.74%	0.73%	0.72%	0.60%
Average	0.54%	0.55%	0.56%	0.57%	0.60%
Average interest rates					
Rational	10.32%	10.26%	10.20%	9.89%	
Behavioral		10.88%	10.93%	10.91%	10.38%
Average	10.32%	10.35%	10.40%	10.43%	10.38%

[†] In the benchmark, 31% of non-college and 15% of college educated are behavioral. That results in an economy-wide fraction of $\lambda = 0.25 \approx 0.62 \times 0.31 + 0.38 \times 0.15$ behavioral consumers. Besides setting this fraction to 0 and 1, we halve and double the benchmark fraction within each education group for a total fraction of $\lambda = 0.12$ and $\lambda = 0.5$.

rises. This composition effect of more behavioral consumers is partially offset by a change in behavior: the amount borrowed and the frequency of bankruptcy filings by each type decline in λ. This reflects the cross-subsidization channel: more behaviorals means that for each rational borrower cross-subsidization payments rise, which makes borrowing more costly. Similarly, borrowing becomes more costly for behaviorals as the amount of cross-subsidization per each behavioral borrower declines. Thus, the amount of debt held by each type declines. Smaller debts are easier to repay and thus individual bankruptcies decline, too.

These patterns explain the small impact on average borrowing interest rates as the share of behaviorals (λ) rises. Although behavioral agents pay higher interest rates for any given fraction λ, rational agents individually pay lower average rates as the fraction λ rises. On average, these effects roughly cancel out and interest rates remain rather stable.

Table A3 reports the effects of changing the extent to which behavioral borrow-

Table A3: Varying the Degree of Over-Optimism

	Degree of Over-Optimism ψ			
	1.00	1.10	1.285†	2.00
Debt-to-income				
Rational	6.31%	6.25%	6.18%	5.92%
Behavioral	6.45%	6.88%	7.73%	10.62%
Average	6.35%	6.40%	6.54%	6.95%
Bankruptcy filings				
Rational	0.52%	0.51%	0.50%	0.46%
Behavioral	0.66%	0.69%	0.73%	0.88%
Average	0.55%	0.55%	0.56%	0.56%
Average interest rates				
Rational	10.28%	10.26%	10.20%	10.06%
Behavioral	10.95%	10.94%	10.93%	10.80%
Average	10.44%	10.43%	10.40%	10.31%

† The benchmark economy is calibrated to $\psi = 1.285$.

ers are over-optimistic. We vary the degree of over-optimism, ψ, between 1 (where the two types are identical and there is no over-optimism) and 2.[68] As behaviorals are convinced they face the same income process as rationals, higher ψ translates into a higher degree of over-optimism. This drives the rise in debt-to-income of behavioral agents, as over-borrowing rises while income falls. Although defaults by over-optimists also rise, they rise by (proportionately) less than debt-to-income due to an increase in filing too late. The larger rise in debt than bankruptcies slightly pushes down average behavioral equilibrium borrowing rates (which does not contradict higher interest rate *schedules*). Being pooled with increasingly behavioral consumers means rational borrowers are pooled with an increasingly risky pool of borrowers. More risky pools are reflected in rising interest rate *schedules*, which drive rationals to borrow less and consequently default less. This results in lower average interest rates for the rational.

These effects show up in the aggregates, albeit more muted. As the degree of

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

over-optimism increases from one to two, borrowing by behaviorals increases by more than 60%, while the economy-wide debt-to-income ratio rises by less than 10%. Even though bankruptcy filings of behavioral consumers increase by more than 30%, average filings remain roughly constant.

These experiments highlight the importance of dis-aggregated data to provide direct evidence on the degree and incidence of over-optimism. Aggregate data provides limited insights especially in the degree of over-optimism. As we vary the extent of over-optimism, there is remarkably little variation in the debt-to-income ratio and virtually none in the average filing rate and interest rate. Thus, a strategy of calibrating the model to aggregate data only would impose little discipline on the parameters related to over-optimism. Instead, additional dis-aggregated data is needed to calibrate the degree and size of over-optimism, corresponding to our strategy outlined in Section 4.

B.2 Robustness of Policy Experiments

The following experiments show that the effects of consumer protection policies discussed in Section 6 are largely robust to changing the fraction and degree of overoptimism as discussed in Section B.1. Table A4 reports the effects of consumer protection policies in an economy where the share of behavioral agents is double: 62% of non-college, 30% of college, and 50% on average. Table A5 reports the same policy experiments in an economy with a higher degree of over-optimism ($\psi = 2$).[69]

Table A4 shows very similar policy effects in an economy with a higher fraction of behavioral consumers. Welfare effects remain qualitatively identical and quantitatively very similar. This is mainly due to the observations described in Section B.1: while averages are significantly affected through a composition effect, changing the fraction of behavioral consumers has little impact on the agents' individual behavior. Consequently, introducing different forms of consumer protection policies has comparable effects on both types of agents. There are two exceptions: First, when default costs are lowered (cf. column (3)), overborrowing *increases* for non-college agents, while in our baseline policy experiment in Table 7 lower default costs decrease these mistakes. With more behavioral borrowers in

[69] Table 7 presents our benchmark results, where $\lambda = 0.25$ and $\psi = 1.285$

Table A4: Policy Experiments with 50% Behavioral Agents

Parameter	(1) BM with $\lambda = 0.5$	(2) Borrow Cost $\uparrow$ $\tau =$ 7.9%	(3) Default Cost $\downarrow$ $\gamma = 50\%$	(4) Debt-to-income $\leq 100\%$	(5) Debt-to-income $\leq 100\%$ if $s < 0.65$
Debt-to-income					
Rational, non-college	6.25%	5.36%	4.65%	5.70%	5.71%
Behavioral, non-college	7.60%	6.53%	5.70%	6.90%	6.90%
Rational, college	5.93%	4.65%	4.32%	3.98%	5.34%
Behavioral, college	7.55%	5.99%	5.40%	5.09%	6.55%
Bankruptcy filings					
Rational, non-college	0.77%	0.77%	1.86%	0.75%	0.75%
Behavioral, non-college	0.89%	0.89%	2.13%	0.87%	0.87%
Rational, college	0.13%	0.12%	0.46%	0.13%	0.14%
Behavioral, college	0.16%	0.15%	0.56%	0.16%	0.18%
Average interest rates					
Rational, non-college	11.69%	12.88%	21.86%	11.36%	11.36%
Behavioral, non-college	11.81%	13.01%	22.85%	11.44%	11.44%
Rational, college	8.72%	9.72%	10.79%	8.60%	8.95%
Behavioral, college	8.77%	9.76%	11.31%	8.59%	8.95%
Paternalistic Welfare					
Rational, non-college		-0.19%	0.64%	-0.06%	-0.06%
Behavioral, non-college		-0.21%	0.65%	-0.08%	-0.08%
Rational, college		-0.21%	0.23%	-0.25%	-0.12%
Behavioral, college		-0.22%	0.25%	-0.26%	-0.15%
Financial Mistakes					
Filing too late, non-college	0.05%	0.22%	0.05%	0.01%	0.01%
Filing too late, college	0.09%	0.05%	0.14%	0.01%	0.03%
Overborrowing, non-college	6.36%	8.80%	7.30%	6.23%	6.23%
Overborrowing, college	9.71%	9.39%	10.37%	8.62%	8.62%

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

the economy, their per capita cross-subsidization decreases. When default costs are lowered, both rational and behavioral borrowers default much more often and hold less debt. In response, interest rate schedules deteriorate, but overoptimists do not lower their debts enough and consequently overborrow more. Nevertheless, committing more financial mistakes does not change the welfare implications of this reform.

Second, contrary to our benchmark policy experiment in Table 7, introducing a DTI limit only for agents with a type score below 0.65 does affect college educated households. This effect is of a technical nature: since there are 30% overoptimists among the college educated, lenders have a type-score prior of 0.7. This prior implies that some bad income shocks are already enough for college educated agents to be subject to the DTI limit that binds for type scores below 0.65. In the benchmark economy, the college prior was 0.85 and hence the threshold was virtually non-binding.

In Table A5, the same policies apply to an economy with behaviorals that are more over-optimistic (and face more downside income risk). Relative to our benchmark calibration, the effects of consumer protection policies remain qualitatively the same and quantitatively quite similar. However, there are two exceptions: First, when default costs are lowered (cf. column (3)), overborrowing *increases* for non-college agents contrary to our baseline policy experiment. With $\psi = 2$, behavioral borrowers overestimate their future ability to repay by more. They roll over too much debt and default too late relative to their informed selves. This effect is more pronounced in a regime where default costs are low. However, committing more financial mistakes does not change the welfare implications of this reform. Both types would happily trade higher equilibrium interest rates for a cheaper option of default and gaining access to better insurance.

Second, similar to the previous robustness exercise, there is a mechanical effect when analyzing DTI limits for type scores below 0.65. When the degree of over-optimism is larger, there are more negative shocks that provide information on the fundamental type of a borrower. Thus, banks can learn faster and update type scores more quickly. Consequently, there are some college educated consumers with type scores below 0.65 that are affected by the policy in column (5).

Table A5: Policy Experiments with a Higher Degree of Over-Optimism ($\psi = 2$)

Parameter	(1) BM with $\psi = 2$	(2) Borrow Cost ↑ $\tau = 7.9\%$	(3) Default Cost ↓ $\gamma = 50\%$	(4) Debt-to-income $\leq 100\%$	(5) Debt-to-income $\leq 100\%$ if $s < 0.65$
Debt-to-income					
Rational, non-college	5.93%	5.04%	4.41%	5.43%	5.70%
Behavioral, non-college	10.09%	8.71%	7.60%	9.13%	9.36%
Rational, college	5.90%	4.51%	4.20%	3.91%	5.46%
Behavioral, college	11.85%	9.54%	8.12%	8.09%	9.90%
Bankruptcy filings					
Rational, non-college	0.71%	0.71%	1.69%	0.69%	0.70%
Behavioral, non-college	1.06%	1.05%	2.42%	1.03%	1.04%
Rational, college	0.13%	0.12%	0.43%	0.13%	0.14%
Behavioral, college	0.25%	0.23%	0.76%	0.23%	0.28%
Average interest rates					
Rational, non-college	11.45%	12.59%	18.97%	11.11%	11.18%
Behavioral, non-college	11.73%	12.84%	20.09%	11.24%	11.29%
Rational, college	8.76%	9.71%	10.32%	8.61%	8.93%
Behavioral, college	8.89%	9.86%	11.04%	8.59%	8.96%
Paternalistic Welfare					
Rational, non-college		-0.19%	0.63%	-0.06%	-0.04%
Behavioral, non-college		-0.22%	0.68%	-0.10%	-0.09%
Rational, college		-0.21%	0.22%	-0.24%	-0.08%
Behavioral, college		-0.22%	0.35%	-0.24%	-0.16%
Financial Mistakes					
Filing too late, non-college	0.24%	0.28%	0.19%	0.05%	0.12%
Filing too late, college	0.20%	0.17%	0.48%	0.03%	0.09%
Overborrowing, non-college	18.43%	20.16%	19.10%	16.21%	17.46%
Overborrowing, college	22.20%	23.08%	26.43%	22.67%	21.04%

C Details of Borrowing Limit Regulation

Here we provide the equations behind the policies considered in Sections 6.4 and 7. *Debt-to-income limits* are implemented by restricting the bond price of too large loans:

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

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

For a general debt-to-income limit, as in Section 6.4, $B(s) = B$ is independent of the type score. For type-score dependent policies discussed in Section 7, $B(s)$ depends on the score. In our policy experiments, we set one limit for all scores below a threshold, $s < \bar{s}$, while consumers above the threshold face no limit. In other words, we set

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

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

D Ergodic Distribution of Type Scores

Table A6: Type-Score Distribution Across Types (CDF)

	Non-College		College		Full Population		
Score	Realist	Behavioral	Realist	Behavioral	Realist	Behavioral	All Types
0.10	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.15	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.20	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
0.25	0.00%	0.01%	0.00%	0.00%	0.00%	0.01%	0.00%
0.30	0.01%	0.05%	0.00%	0.00%	0.01%	0.04%	0.01%
0.35	0.05%	0.17%	0.00%	0.00%	0.03%	0.13%	0.06%
0.40	0.19%	0.54%	0.00%	0.00%	0.11%	0.42%	0.19%
0.45	0.61%	1.50%	0.00%	0.01%	0.35%	1.16%	0.55%
0.50	1.80%	3.83%	0.01%	0.02%	1.03%	2.96%	1.51%
0.55	4.89%	9.02%	0.02%	0.09%	2.80%	6.97%	3.84%
0.60	12.71%	20.12%	0.09%	0.29%	7.28%	15.58%	9.35%
0.65	31.54%	42.23%	0.33%	0.96%	18.12%	32.79%	21.77%
0.70	69.50%	79.35%	1.56%	3.54%	40.27%	62.01%	45.69%
0.75	87.92%	93.29%	6.08%	10.95%	52.71%	74.46%	58.13%
0.80	96.78%	98.60%	21.85%	31.06%	64.54%	83.15%	69.18%
0.85	99.42%	99.80%	72.30%	80.99%	87.75%	95.50%	89.68%
0.90	99.94%	99.98%	93.95%	96.81%	97.36%	99.26%	97.83%
0.95	100.00%	100.00%	99.42%	99.77%	99.75%	99.95%	99.80%
1.00	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%
Overall Population Shares							
	42.78%	19.22%	32.3%	5.7%	75.08%	24.92%	