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Contents

Preface

This dissertation studies questions in macroeconomics and more specifically consumer finance. It consists of two self-contained chapters. While each chapter studies a different question, they share common objects of interest and similar methodologies.

The topics that I study in this thesis relate to how households make financial decisions in terms of saving and borrowing and the role of bankruptcy in smoothing consumption. Based on this understanding of household behavior I then ask how (bankruptcy) policy should be shaped. The first chapter focuses on the interaction of two loan types in the presence of asymmetric information. The second examines how risk differs across marital status and how this affects bankruptcy regulation.

In terms of methodology I employ quantitative macroeconomic models. They are based on the Huggett-model with households facing income and expense risk. Households may save and borrow to smooth consumption. In addition, they may default on their loans. Both chapters use this common framework and each adds other dimensions of complexity. I calibrate the resulting models to data and then use the calibrated model to conduct policy experiments. In the following, I give an overview of the two chapters.

Chapter 1 is titled "The Payday Loan Puzzle: A Credit Scoring Explanation" and is co-authored with Tsung-Hsien Li. This chapter studies the so-called payday loan puzzle. A payday loan is a type of short-term loan which is common in the United States. These loans carry interest rates that are much higher than those for credit cards. Previous literature has found that two-thirds of individuals who use both credit cards and payday loans still have liquidity left on their credit cards when taking out the payday loan. This behavior results in significant monetary costs and has thus been termed a puzzle. We formally propose the explanation that households use payday loans in order to protect their credit scores. A credit score is a statistic used by lenders to assess a borrower's creditworthiness. These scores have large importance in the United States as they can influence credit card and mortgage interest rates or even play a role in the job application process. While using credit cards affects one's credit score, using payday loans normally does not. In essence, we hypothesize that using payday loans instead of credit cards leads to reputational benefits over time at the cost of higher interest fees in the present.

To quantitatively examine this hypothesis, we build a Huggett-type model with the option of default that includes two assets (bank loans and payday loans) as well as asymmetric information. We show that our calibrated model can account for 40% of the empirically identified payday loan borrowers with liquidity left on their credit cards. We can also match the magnitude of monetary costs due to this seeming pecuniary mistake. We then turn to the policy implications of our model. Payday loans are a hotly debated topic in the United States. Critics have argued for an outright ban of payday loans because of their high costs. To inform the policy debate over payday lending, we assess the welfare implications of several policy counterfactuals. We find that either banning payday loans or increasing their default costs results in aggregate welfare losses.

Chapter 2, titled "The Role of Marital Status for the Evaluation of Bankruptcy Regimes", looks at how marital status affects consumer bankruptcy regulation. There exists large heterogeneity in bankruptcy rates across marital status in the United States. Conditional on many socio-economic controls, single, and in particular divorced households, are much more likely to default than married ones. At the same time, the consumer finance literature has emphasized the importance of income and expense risk for the evaluation of different bankruptcy regimes in terms of leniency. Single and married households differ in the risks they face. However, the structural consumer default literature has failed to differentiate between single and married households until now.

In this chapter, I build the first quantitative consumer default model that explicitly models singles and couples. I calibrate my model to the United States in 2019 and estimate (medical) expense shocks separately for single and married individuals. My calibrated model generates large differences in bankruptcy rates across marital status. Next, I examine how the preferred degree of bankruptcy leniency differs between singles and couples. There are several channels at work: Differences on the income side between singles and couples cause couples

to prefer a stricter bankruptcy regime due to intra-household insurance such as spousal labor supply. However, increased risk for couples due to divorce and on the expense side outweigh the first channel. The net effect is that couples prefer more lenient bankruptcy than singles. My findings suggest that marital status is important to take into account for the evaluation of bankruptcy regimes.

Chapter 1

The Payday Loan Puzzle: A Credit Scoring Explanation

Joint work with Tsung-Hsien Li

1.1 Introduction

Agarwal, Skiba, and Tobacman (2009) observe that two-thirds of individuals who use both credit cards and payday loans have at least $1,000 of credit card liquidity left when taking out a payday loan.[1] This behavior is seemingly puzzling as payday loans carry very high interest rates corresponding to annualized percentage rates of several hundred percent, compared to 10 to 30 percent on credit cards. The authors calculate that this seeming pecuniary mistake is very costly: these people could have saved on average $200 over a year by borrowing up to their credit card limits before taking out payday loans. This phenomenon has been termed the "Payday Loan Puzzle."

Why do households take out expensive payday loans when they have far cheaper credit options available? Various behavioral explanations, such as self-control problems and financial illiteracy, have been put forward. In this paper, we propose a novel rational explanation for the payday loan puzzle, inspired by the following interview of an actual payday lender:

[1] A payday loan is a short-term unsecured loan with a duration of a few weeks for a typically small amount of around $300. In the SCF 2010, around 5% of households used payday loans in the previous year. About 60% of payday loan borrowers possess credit cards. See, for example, Elliehausen and Lawrence (2001).

> *"Why are people taking out [payday] loans instead of using their cards?" Ranney told me, "This guy was implying that these people weren't smart enough to make the 'right' decision. I laughed in his face.* ***'They're protecting the card!'*** *I told him. [...]"* ***Whereas failure to repay a payday loan won't affect a consumer's credit score, failure to repay a credit card will.***
>
> — Servon (2017): *The Unbanking of America*[2]

Our proposed "reputation protection" hypothesis is that people do not exhaust their credit card limits because they want to protect their credit scores. A credit score is a statistic computed by credit bureaus to assess a person's default risk.[3] Borrowing or defaulting on credit cards will affect one's credit score, while payday lenders in the U.S. usually do not report to credit bureaus (Consumer Financial Protection Bureau, 2017).[4] People care about their credit scores as they influence credit access, credit costs, mortgage terms, and even job application prospects in the future. Therefore, using payday loans to protect one's credit score leads to dynamic reputational benefits at the static cost of higher interest fees.

To better understand the reasons behind the payday loan puzzle and to formalize the above hypothesis, we extend the type scoring framework of Chatterjee, Corbae, Dempsey, and Ríos-Rull (2020). The authors study a Huggett-type model with consumer default and asymmetric information. Households differ in their degrees of patience measured by discount factors (called their "types"). These factors influence their default behavior and thus their riskiness as borrowers. However, banks are unable to observe household types directly. As a result, banks resort to using "type scores" to infer the probability of each individual being patient with a high discount factor (the good type). A type score thus represents an individual's reputation in the credit markets and is analogous to a credit score in practice.[5]

We extend their framework by adding a second debt option (payday loans)

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[2] Servon was interviewing Tim Ranney, a payday lender, and Ranny was sharing a conversation he had with a risk manager at one of the largest credit card issuers in the U.S.

[3] The most well-known credit score in the U.S. is the FICO score, 35% of which is determined by the payment history and 30% by the debt burden.

[4] In line with our hypothesis, Bhutta, Skiba, and Tobacman (2015) empirically document that payday loans have no impact on credit scores.

[5] Chatterjee et al. (2020) show that there exists a mapping from the type score economy to a credit score economy under some sufficient conditions.

and a second default option on only payday loans. Thus, in addition to bank loans, households in our model can also borrow using payday loans offered by the second type of financial intermediary called payday lenders. Households can default in two ways: (1) "formal default" where households default on both bank and payday loans;[6] and (2) "payday default" where households default selectively only on their payday loans. Default costs include filing fees, utility loss (stigma), and temporary exclusion from the respective asset markets. In equilibrium, payday loans have higher interest rates compared to bank loans because of higher default premia and operating costs. Crucially, banks cannot observe the payday loan choices of households. Payday loans thus introduce hidden actions into the price setting and type score updating problem of banks. To our knowledge, we are the first to explicitly model payday loans using a two-asset structure and two default options.

In our model, a dynamic trade-off emerges between the short-run costs of payday loans and the long-run reputational credit score gains. Households trade off between the marginal benefit of maintaining one's type scores versus the marginal cost of borrowing on more expensive payday loans. The intuition behind the type score protection is as follows. Banks cannot observe a household's type and its payday loan usage. If a household is hit by a low income shock and borrows using bank loans to smooth consumption, banks regard this as being indicative of impatience and thus downgrade the type score. Taking up payday loans instead helps protect against being misclassified in the current period. Moreover, it also lowers the probability of a type score downgrade due to default on bank loans in the future in case of sufficiently low future income shocks. We are the first to formally examine the reputation protection explanation for the payday loan puzzle in a theoretical model.

Limited information of banks regarding households' types and payday loan choices gives rise to cross-subsidization in the bank loan market. Conditional on the same level of bank borrowing, impatient households or payday loan borrowers are more likely to default. However, banks cannot observe either a household's type or payday loan usage. This imperfect information restricts banks from designing contracts conditioned on these two characteristics. Both impatient households and payday loan borrowers thus face cheaper borrowing rates than the actuarially fair rates when banks have full information. As a

[6] This is modeled in line with Chapter 7 bankruptcy in the U.S. which entails the liquidation of non-exempt assets in return for debt dischargement.

result, impatient households (payday loan borrowers) are subsidized by patient households (non-payday loan borrowers) in the bank lending market.

To understand the payday loan puzzle documented in Agarwal et al. (2009), we calibrate our model to the U.S. households in 2004. Most parameters are exogenously determined by direct empirical evidence or estimates from the literature. We internally calibrate the stigma costs of defaults to match default rates in the bank and payday markets. Our calibrated model can account for various untargeted moments, such as the fraction of payday loan borrowers and the average interest rate on payday loans.

Our calibrated model endogenously gives rise to the reputation protection channel: households invest in their type scores by paying higher interest costs on payday loans. We can quantitatively account for 40% of the empirically identified payday loan borrowers who have not exhausted their credit cards yet. We can also match the magnitude of the monetary costs. Neither of these moments was targeted in the calibration.[7] In particular, the model predicts average annual monetary costs of \$230, which is similar to its empirical counterpart of \$200 as calculated by Agarwal et al. (2009). Using our calibrated model, we are the first to generate and quantitatively match the empirically identified payday loan puzzle.

Payday loans have been a controversial subject of debate in the U.S. in recent years. Critics of payday loans have focused on the high costs of these loans and have argued for outright payday loan bans.[8] However, we show that payday loans serve an essential insurance purpose even in the presence of these high costs. We are the first to inform the payday loan policy debate in a structural framework by conducting a series of counterfactual policy experiments.

First, we investigate the effects of limiting the maximum payday loan size, a quantity cap, and an outright ban of payday loans. We find that a quantity cap decreases overall welfare. However, there is heterogeneity across households: impatient households lose while patient ones gain. Impatient households are more likely to borrow larger payday loans and are thus more heavily affected by the quantity cap. In addition, the quantity cap imposes less unobservable options on payday loans. This reduction in hidden actions enables banks to

[7] As mentioned previously, the unaccounted 60% of the puzzle occurrence could be potentially explained by other behavioral explanations.

[8] For example, 16 states and the District of Columbia in the U.S. either prohibit payday loans or impose limits, while 23 states allow payday lending (Consumer Federation of America, 2021).

better infer payday loan usage of households, thus reducing the amount of information asymmetry in the bank loan market. As a result, banks can better identify households' discount factors, leading to a decline in cross-subsidization of impatient by patient households. In contrast to the quantity cap, a full ban on payday loans is welfare-reducing for both types of households. The reason for the welfare loss is the reduction in available insurance. Both impatient and patient households use payday loans to smooth idiosyncratic shocks without harming their type scores. With a full ban, the insurance loss outweighs the gains from reduced cross-subsidization for patient households. These results imply that current regulatory efforts in certain U.S. states to ban payday loans may be misguided in the sense that they end up hurting all households.[9]

Second, we examine the implications of increasing either the formal or payday default cost. The increase in default costs is calibrated to reflect the increase in Chapter 7 filing costs after the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) in the U.S.[10] We find that increasing formal default costs leads to a welfare gain, whereas increasing payday default costs leads to a welfare loss for both types of households. Higher default costs make it harder to *smooth consumption across states* by defaulting, but easier to *smooth consumption over time* by borrowing through lower default premia (Zame, 1993). In equilibrium, households prefer smoothing across states by defaulting on payday loans while smoothing over time by borrowing bank loans for three reasons: (1) defaulting on payday loans does not directly affect a household's type score, whereas formally defaulting on a bank loan does; (2) interest rates for bank loans are much lower than payday loans; and (3) payday default costs are lower than formal default costs. Higher formal (payday) default costs exactly help (hamper) households in achieving smoothing over time (across states).

The rest of the paper is organized as follows. Section 1.2 gives an overview of the related literature. Section 1.3 details the model framework. Section 1.4 presents the calibration of the model. Section 1.5 illustrates the fundamental mechanism of pooling and cross-subsidization in our framework. In Section

[9] For example, Morse (2011) uses natural disasters to identify a causal, positive relationship between welfare and access to payday loans. In other words, banning payday loans results in a welfare loss.

[10] The 2005 BAPCPA was the most significant reform of bankruptcy law in recent years. Among other changes, it significantly increased the total out-of-pocket filing costs. See also Albanesi and Nosal (2020).

1.6, we discuss in detail the payday loan puzzle and the reputation protection channel in our model. Section 1.7 presents the policy experiments and Section 1.8 concludes with some potential extensions.

1.2 Related Literature

In this section, we discuss the literature related to our paper. The consumer finance literature (both empirical and theoretical) is extensive; thus, we will only focus on the papers most directly related to our own. We start by discussing papers that we build on in terms of the underlying methodology and then briefly summarize the literature on payday loans.

Our theoretical framework is based on the type scoring framework developed by Chatterjee et al. (2020). In their paper, they build on the consumer default workhorse models developed by Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007) and Livshits, MacGee, and Tertilt (2007) in which households are allowed to default on their loans as insurance against idiosyncratic risk.[11] Both Chatterjee et al. (2007) and Livshits et al. (2007) assume that lenders are fully informed about all household characteristics that affect repayment in the next period. Chatterjee et al. (2020) depart from this assumption and introduce heterogeneity across households in the form of different discount factors, which are unobservable by banks. As the patience of households affects their loan repayment probability, banks try to infer households' types by computing an individual-specific type score. This score denotes the Bayesian assessment by banks of individual type based on observable household behavior. Our paper extends this model by introducing a second asset and an additional default option. In addition, banks cannot observe payday loans and default and thus face hidden actions.

Our paper is also closely related to the empirical literature on the seeming pecuniary mistakes in using payday loans. Using matched credit card and payday loan data, Agarwal et al. (2009) document that many borrowers use payday loans when they still have sufficient credit left on their credit cards, even though

[11] Some papers extend the standard consumer default framework by incorporating behavioral components. For example, Nakajima (2017) considers households with temptation and analyzes the welfare implications of the 2005 BAPCPA. Exler, Livshits, MacGee, and Tertilt (2020) introduce over-optimism of households about future income. See also Exler and Tertilt (2020) for a complete survey.

payday loans carry much higher interest rates. They compute that this behavior is very costly and leads to monetary costs of several hundred U.S. dollars over one year. They coin this finding the "Payday Loan Puzzle." Furthermore, Carter, Skiba, and Tobacman (2011) look at a dataset of credit union members and their payday loan borrowing behavior. They also find a pecuniary loss due to the usage of payday loans instead of cheaper alternatives similar to the previous paper. We contribute to this literature by generating the payday loan puzzle in a theoretical model and offering a rational explanation for part of its occurrence.

Payday loans and their effects on consumers are a hotly debated regulatory topic in the U.S. The literature on the effects of payday loans on consumers is in disagreement about its sign. Using household panel survey data, Zinman (2010) finds that restricting access to payday loans leads consumers to shift to bank overdrafts and late payments. The result is a decline in the financial health of affected households and an overall harmful effect of restricting payday loans. Similarly, Morse (2011) uses natural disasters and estimates that access to payday lenders increases welfare. Morgan, Strain, and Seblani (2012) find that the banning of payday lending leads to an increase in bounced checks and overdraft fees. Bhutta, Goldin, and Homonoff (2016) find that consumers switch to other high-cost alternatives in response to payday loan bans. These authors stress that payday loans are instrumental for households to mitigate the negative effects of transitory income or expenditure shocks, especially when access to the mainstream financial system is impaired.

On the other hand, many authors point out that using payday loans can further worsen households' financial situations. Skiba and Tobacman (2019) estimate that using payday loans significantly increases bankruptcy rates by depressing the cash flow of households. Melzer (2011) finds that access to payday loans worsens the ability of households to pay mortgages, rent, and utility bills. Carrell and Zinman (2014) use exogenous variation in payday loan access for military personnel to estimate that usage of payday loans decreases job performance, retention, and readiness. Campbell, Martínez-Jerez, and Tufano (2012) find that access to payday lending increases rates of involuntary bank account closures. We contribute to this literature by offering a theoretical framework in which we jointly model mainstream financial and payday loans as well as their interaction with credit scores. We then use our framework to conduct counterfactual policy exercises, such as banning payday loans, and investigate the resulting welfare implications for households.

Our paper is also related to Exler (2020). He examines the welfare impact of different policy alternatives to regulate small-dollar loans. He builds and calibrates a quantitative model of unsecured lending where individuals can declare bankruptcy or become delinquent. His findings suggest welfare improving changes to the legislation proposed by the Consumer Financial Protection Bureau (CFPB). In contrast to our approach, he considers only one asset and does not model credit scores. Saldain (2021) considers a model of only payday loans with behavioral households and studies policy regulations on payday lending.

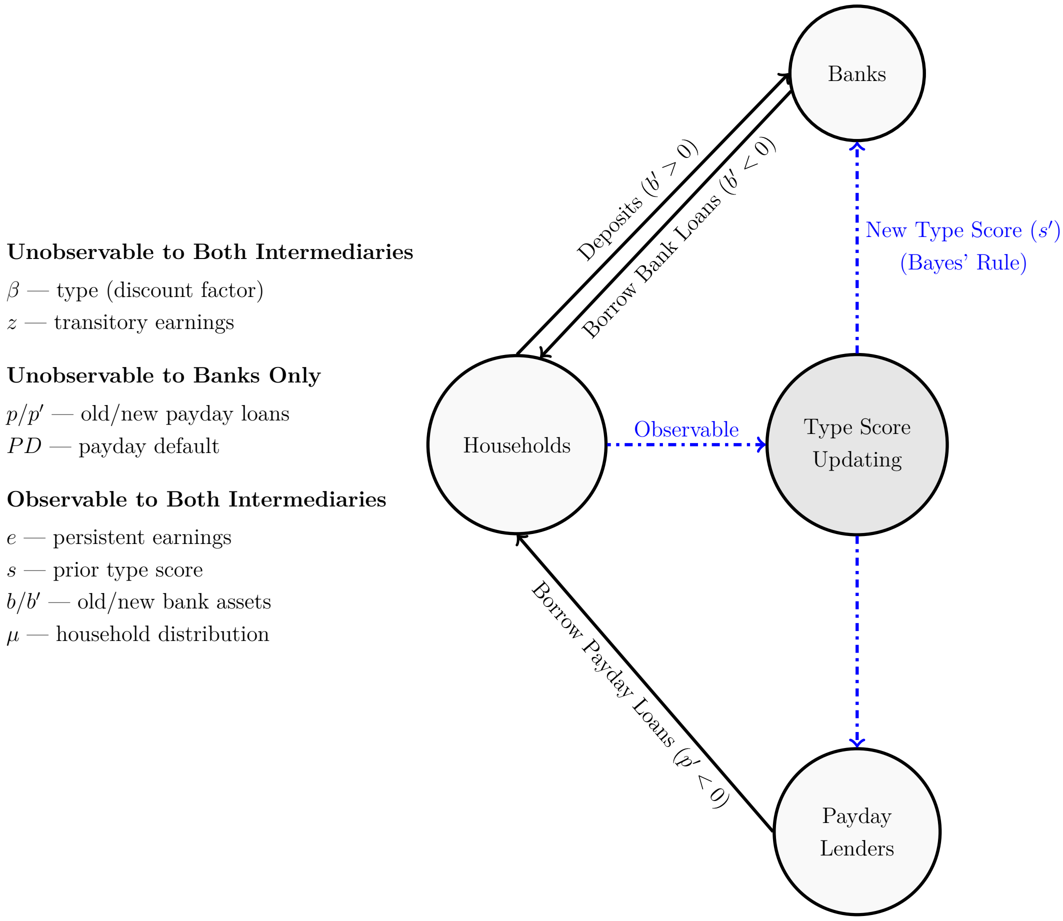
1.3 The Model

Time is discrete and infinite. We follow the convention of dynamic programming that the time subscript is removed, and the next-period variable is expressed with prime $'$. The market is incomplete. There is a measure one of rational households populating the economy. In addition, there exist two financial intermediaries, banks and payday lenders, which operate in perfectly competitive markets. Both offer lending services in one-period unsecured loans. Banks also provide saving services. The layout of the economy is illustrated in Figure 1.1.

In every period, households survive at a rate ρ, and those who die are replaced by newborns. Households receive persistent earnings e following a stationary finite-state Markov process $Q^e(e'|e)$ and transitory earnings z determined by an i.i.d. process $Q^z(z)$. All income realizations are independent across individuals. There are two types of households: impatient households with a low discount factor β_L and patient households with a high discount factor β_H. A household's discount factor follows a stationary two-state Markov process $Q^\beta(\beta'|\beta)$ and evolves independently across individuals. We call a household's discount factor her type.

Households derive utility from consumption c. They can either borrow or save an amount b' at the discount price q_b with banking institutions. Furthermore, they may also take out payday loans p' at the discount price q_p. These actions are illustrated with the solid arrows in Figure 1.1. At the beginning of each period, if a household has any kind of debt, she can choose to repay ($d = R$) or default. There are two default options available: formal default ($d = FD$)

Figure 1.1: Layout of the Economy and Information Structure



and payday default ($d = PD$). Formal default discharges all debts (including potential payday loans) but incurs the out-of-pocket bankruptcy costs κ_{FD} (e.g., attorney fees) and stigma (utility) costs ξ_{FD}. In addition, no saving or borrowing is possible in the filing period. Alternatively, she may choose payday default to selectively discharge her payday loan only at the cost of filing fees κ_{PD} and stigma costs ξ_{PD}. Compared to formal default, she becomes excluded only from the payday lending market, and potential bank loans still need to be repaid, but she retains access to the bank asset market.[12]

Banks can observe households' persistent earnings e, bank asset position b, bank asset choice b', formal default FD, and household distribution μ. On the contrary, they cannot observe households' transitory earnings z, payday

[12]Note that, compared to most papers in the consumer finance literature, there is no long-term exogenous exclusion imposed in our model.

loan position p, payday loan choice p', payday default ($d = PD$), and discount factors β. We denote (e, b, s) as the bank-observable state ω_b. This information structure is summarized on the left-hand side in Figure 1.1. As all unobservable variables are relevant for the repayment probability of loans in the next period, banks would like to infer them. While banks cannot infer transitory earnings z as they are i.i.d. across time and households, the other variables can be.

For a household's payday loan position p, we assume that banks are not able to track it at an individual level, but banks know the aggregate distribution of payday loans in the population (rational expectations). As a result, banks exploit the cross-sectional distribution of households to form their expectation about a household's payday loan position.[13] Banks then handle unobservable payday loan choices p' by summing them out. In addition, banks cannot observe whether payday loans are repaid. Hence, they cannot distinguish between full repayment or payday default by households. These two choices are accordingly subsumed under non-formal default ($\tilde{d} = NFD \equiv R \vee PD$).

Households' discount factors are unobservable to financial intermediaries. Banks infer these factors using type scores s, which denote the probability of being patient. Past actions are informative about a household's discount factor as it follows a persistent process. The prior assessment of a household being patient at the beginning of a period is denoted as $s \equiv \mathbb{P}(\beta_i = \beta_H)$. Given bank-observable states ω_b and choices $(\tilde{d}, b')$, banks will update a household's type score s using Bayes' rule each period. The posterior type score is denoted as $s' = \psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$ where superscripts denote actions and variables in parentheses denote states. As the updated type score may not lie on the type score grid, it is assigned to the nearest grid points using the function $Q^s(s'|\psi)$.[14] The type score updating process is indicated by the dashed arrows in Figure 1.1. Thus, the bank loan pricing function $q_b^{(NFD,b')}(\omega_b)$ will be affected by an individual's observable choices and characteristics, including type scores.

Payday lenders are assumed to be more informed than banks. In addition to what banks can observe, payday lenders can certainly tell payday loan decisions. This information structure is also summarized on the left-hand side in Figure 1.1. For simplicity, we assume that payday lenders use the identical type scores

[13] In principle, it is also possible to assume that banks form a joint score over type and payday loan choices $s(\beta, p)$ for each household.

[14] To be precise, s' will be randomly assigned to one of the two nearest points between which s' lies, with probabilities inversely proportional to the relative distance of s' to the respective grid points. This assignment is captured by the function $Q^s(s'|\psi)$.

as banks.[15]

The rest of the section is structured as follows. Section 1.3.1 summarizes the timing in each period. Section 1.3.2 details the household's maximization problem. Section 1.3.3 presents the problems of both financial intermediaries. In particular, type score updating is discussed in Section 1.3.3. Section 1.3.4 shows the evolution of the cross-sectional distribution of households. In Section 1.3.5, we close the section by defining the equilibrium.

1.3.1 Timing

The timing in every period is summarized as follows:

1. Households begin each period with state (β, z, ω_b, p).

2. Given bank prices $q_b^{(NFD,b')}(\omega_b)$ and payday prices $q_p^{(R,b',p')}(\omega_b)$, households choose to either repay all debt $d = R$, default on the payday loan only $d = PD$, or formally default on both loans $d = FD$.

   - If $d = R$, they also choose b' and p' and consume $c^{(R,b',p')}$.
   - If $d = PD$, they also choose b' and $p' = 0$ and consume $c^{(PD,b',0)}$.
   - If $d = FD$, they consume the leftover earnings $c^{(FD,0,0)}$.

3. Based on bank-observable states ω_b and choices $(\tilde{d}, b')$, banks update their type scores from prior s to posterior $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$.

4. β', z', e', and s' are drawn from $Q^\beta(\beta'|\beta)$, $Q^z(z')$, $Q^e(e'|e)$, and $Q^s(s'|\psi)$. Newborn households begin with discount factor β' drawn from the initial distribution G_β, transitory earnings z' from G_z, persistent earnings e' from G_e, no bank or payday loan assets $(b', p') = (0, 0)$, and a type score s' consistent with G_β.

1.3.2 Households

Households take as given the bank and payday loan pricing functions $q_b^{(NFD,b')}(\omega_b)$ and $q_p^{(R,b',p')}(\omega_b)$ as well as the type scoring function $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$. Households can

[15] In principle, payday lenders can form another "type score" using their richer information set compared to banks. This simplifying assumption is meant to keep computation numerically tractable. Nonetheless, payday lenders can still better predict the repayment probability than banks in our economy.

choose between repayment ($d = R$), defaulting on payday loans only ($d = PD$), or formally defaulting on both bank and payday loans ($d = FD$).

Following Chatterjee et al. (2020), we introduce the action-specific utility shocks. These shocks are i.i.d. across time and households. For each action (d, b', p') and household, an unobservable additive utility shock $\epsilon^{(d,b',p')}$ is drawn from an extreme value distribution. These shocks capture other unobservable heterogeneity that is not explicitly modeled in a reduced but tractable way. Policy functions also become probabilistic with these shocks. Without such randomness, households' actions are perfectly informative about their true types.

The value function is thus given by:

$$V(\epsilon, \beta, z, \omega_b, p) = \max_{(d,b',p')} v^{(d,b',p')}(\beta, z, \omega_b, p) + \epsilon^{(d,b',p')}, \tag{1.1}$$

where $\epsilon^{(d,b',p')}$ is drawn from the following extreme value distribution $EV(\epsilon)$:

$$EV(\epsilon) = \exp\left\{-\exp\left(-\frac{\epsilon - \mu_\epsilon}{\alpha}\right)\right\}, \tag{1.2}$$

where $\alpha > 0$ determines the variance of the shock and $\mu_\epsilon = -\alpha\gamma_E$ makes the shock mean zero and γ_E is the Euler's constant.[16]

The conditional value function is given by:

$$\begin{aligned} v^{(d,b',p')}(\beta, z, \omega_b, p) = {} & u\left(c^{(d,b',p')}(z, \omega_b, p)\right) - \xi_{PD} \cdot \mathbb{I}_{[d=PD]} - \xi_{FD} \cdot \mathbb{I}_{[d=FD]} \\ & + \beta\rho \cdot \sum_{(\beta',z',e',s')} Q^\beta(\beta'|\beta) \cdot Q^z(z') \cdot Q^e(e'|e) \cdot Q^s(s'|\psi) \cdot W(\beta', z', \omega_b', p'), \end{aligned} \tag{1.3}$$

where the utility function defined on consumption $u(c)$ is additively separable over time, continuous, increasing, and concave; ξ_{PD} and ξ_{FD} represents the stigma costs for payday and formal default; $\mathbb{I}$ denotes the indicator function equal to one if the condition in the squared parentheses is true; W is the unconditional value function which will be defined below; and consumption

[16] Note that the noise of extreme value shocks is not the reason why our model is able to generate the payday loan puzzle. In fact, we control for it while identifying the puzzle. Refer to Section 1.6.1 for details.

$c^{(d,b',p')}(z, \omega_b, p)$ is defined as:

$$\begin{cases} e \cdot z + b + p - q_b^{(NFD,b')}(\omega_b) \cdot b' - q_p^{(R,b',p')}(\omega_b) \cdot p', & \text{if } (d, b', p') = (R, b', p') \\ e \cdot z - \kappa_{PD} + b - q_b^{(NFD,b')}(\omega_b) \cdot b', & \text{if } (d, b', p') = (PD, b', 0) \\ e \cdot z - \kappa_{FD}, & \text{if } (d, b', p') = (FD, 0, 0) \end{cases}, \tag{1.4}$$

where κ_{PD} and κ_{FD} denote the out-of-pocket bankruptcy costs for payday and formal default.[17]

Let the set of feasible actions be defined as:

$$\mathcal{F}(z, \omega_b, p) = \left\{(d, b', p') | c^{(d,b',p')}(z, \omega_b, p) > 0\right\}. \tag{1.5}$$

Under the distributional assumption on the utility shocks in Equation (1.2), the choice probabilities take the following form:[18]

$$\sigma^{(d,b',p')}(\beta, z, \omega_b, p) = \begin{cases} \frac{\exp\left\{v^{(d,b',p')}(\beta,z,\omega_b,p)/\alpha\right\}}{\sum_{(\hat{d},\hat{b}',\hat{p}')\in\mathcal{F}} \exp\left\{v^{(\hat{d},\hat{b}',\hat{p}')}(\beta,z,\omega_b,p)/\alpha\right\}} & \text{if } (d, b', p') \in \mathcal{F}(z, \omega_b, p) \\ 0 & \text{otherwise} \end{cases}. \tag{1.6}$$

The unconditional value function is then given by:

$$\begin{aligned} W(\beta, z, \omega_b, p) &= \mathbb{E}_\epsilon V(\epsilon, \beta, z, \omega_b, p) \\ &= \alpha \cdot \ln\left(\sum_{(d,b',p')\in\mathcal{F}(\beta,z,\omega_b,p)} \exp\left\{\frac{v^{(d,b',p')}(\beta, z, \omega_b, p)}{\alpha}\right\}\right). \end{aligned} \tag{1.7}$$

We use $\mu(\beta, z, \omega_b, p)$ to denote the cross-sectional distribution of households.

1.3.3 Financial Intermediaries

In this section, we detail the financial intermediaries. Section 1.3.3 presents the banking sector and Section 1.3.3 outlines the payday lenders.

[17] There are two technical assumptions. First, we assume for computational reasons that households can only take out payday loans if they also borrow in the banking sector. Second, we assume that default is restricted to households who have debts larger than the respective monetary bankruptcy costs. For example, formal default is feasible only if $b + p < -\kappa_{FD}$.

[18] See, for example, Rust (1987).

Banks

Banks can borrow from the international credit market at risk-free interest rate r_f. The bank's profit $\pi_b^{(NFD,b')}(\omega_b)$ for a contract (NFD, b') is given by:

$$\pi_b^{(NFD,b')}(\omega_b) = \begin{cases} \rho \cdot \frac{\mathbb{P}_b^{(NFD,b')}(\omega_b)\cdot(-b')}{1+r_f} - q_b^{(NFD,b')}(\omega_b) \cdot (-b') & \text{if } b' < 0 \\ q_b^{(NFD,b')}(\omega_b) \cdot b' - \rho \cdot \frac{b'}{1+r_f} & \text{if } b' \geq 0 \end{cases}, \tag{1.8}$$

where ρ is the survival probability and $\mathbb{P}_b^{(NFD,b')}(\omega_b)$ denotes the repayment probability of a contract (NFD, b') conditional on bank-observable states ω_b. Given perfect competition, the zero-profit condition implies for each contract that:

$$q_b^{(NFD,b')}(\omega_b) = \begin{cases} \rho \cdot \frac{\mathbb{P}_b^{(NFD,b')}(\omega_b)}{1+r_f} & \text{if } b' < 0 \\ \frac{\rho}{1+r_f} & \text{if } b' \geq 0 \end{cases}. \tag{1.9}$$

Recall that banks cannot observe discount factors β, transitory earnings z, payday loan holdings and choices (p, p'), as well as the exact choice of repayment or payday default $(d = PD \vee R)$. To determine the repayment probability $\mathbb{P}_b^{(NFD,b')}(\omega_b)$, banks solve an inference problem over these unobservables in three steps.

1. Filter out unobservable states and actions (p, p', R, PD) to obtain the choice probabilities of bank-observable actions $\tilde{\sigma}_b^{(\tilde{d},b')}(\beta, z, \omega_b)$.
2. Assess the probability that an individual is patient tomorrow β' given bank-observable state ω_b and choices $(\tilde{d}, b')$, i.e., the posterior type score $s' = \psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$.
3. Compute the individual's repayment probability given transition over ω_b for each possible β'. Then, use the weighted sum over β' to compute $\mathbb{P}_b^{(NFD,b')}(\omega_b)$.

In the first step, banks filter out payday loan holdings p using the household distribution μ and sum out payday loan choices p' as follows:

$$\sigma_b^{(d,b')}(\beta, z, \omega_b) = \sum_{p'} \underbrace{\sum_p \sigma^{(d,b',p')}(\beta, z, \omega_b, p) \cdot \frac{\mu(\beta, z, \omega_b, p)}{\sum_{\hat{p}} \mu(\beta, z, \omega_b, \hat{p})}}_{\equiv \hat{\sigma}_b^{(d,b',p')}(\beta,z,\omega_b)}, \tag{1.10}$$

where the last fraction denotes the marginal distribution of p conditional on (β, z, ω_b). The idea is straightforward: since banks have rational expectations, they deal with the unobservables by weighting them with the distribution of unobservables conditional on the observables. Banks then form the probability of formal default ($\tilde{d} = FD$) versus non-formal default ($\tilde{d} = NFD \equiv R \vee PD$) to obtain the choice probabilities of bank-observable actions as follows:

$$\tilde{\sigma}_b^{(\tilde{d},b')}(\beta, z, \omega_b) = \begin{cases} \sigma_b^{(d,b')}(\beta, z, \omega_b) & \text{if } \tilde{d} = FD \\ \sum_{d \in \{R,PD\}} \sigma_b^{(d,b')}(\beta, z, \omega_b) & \text{if } \tilde{d} = NFD \end{cases}. \tag{1.11}$$

Accordingly, the feasible set from the bank's perspective is defined as:

$$\tilde{\mathcal{F}}_b(\beta, z, \omega_b) = \left\{ (\tilde{d}, b') \middle| \tilde{\sigma}_b^{(\tilde{d},b')}(\beta, z, \omega_b) > 0 \right\}. \tag{1.12}$$

In the second step, an individual's type score update is computed using Bayes' rule:[19]

$$\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b) = \begin{cases} \sum_z Q^z(z) \cdot \sum_\beta Q^\beta(\beta'|\beta) \cdot \frac{\tilde{\sigma}_b^{(\tilde{d},b')}(\beta,z,\omega_b) \cdot s(\beta)}{\sum_{\hat{\beta}} \tilde{\sigma}_b^{(\tilde{d},b')}(\hat{\beta},z,\omega_b) \cdot s(\hat{\beta})} & \text{for } (\tilde{d}, b') \in \tilde{\mathcal{F}}_b \\ \sum_\beta Q^\beta(\beta'|\beta) \cdot s(\beta) & \text{for } (\tilde{d}, b') \notin \tilde{\mathcal{F}}_b \end{cases}, \tag{1.13}$$

where $s(\beta_L) \equiv 1 - s(\beta_H)$. For completeness, the second case in Equation (1.13) handles the score updating for an infeasible action. The updating process is intuitive: banks' prior belief s is updated with the relative choice likelihood of observable actions across types $\left(\tilde{\sigma}_b^{(\tilde{d},b')} \middle/ \sum_\beta \tilde{\sigma}_b^{(\tilde{d},b')} \cdot s \right)$, and with the exogenous transition of discount factors Q^β and transitory earnings Q^z. The posterior type score s' is denoted by $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$. There are two observations: (1) rebuilding type scores is costly due to priors; and (2) the updating process is dominated by priors when banks are certain about households' types. As s' may not lie on the score grid, we randomly assign it to one of the two nearest points. This assignment is characterized by the function $Q^s(s'|\psi)$. Refer to Appendix 1.A for details.

In the final step, the next-period repayment probability of a contract (NFD, b')

[19] Note that $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b) \in [0, 1]$ and its value is bounded by the transition probability of becoming patient for all ω_b and $(\tilde{d}, b')$.

for banks is computed as:

$$\mathbb{P}_b^{(NFD,b')}(\omega_b) = \sum_{(\beta',z',e',s')} s'(\beta') \cdot Q^z(z') \cdot Q^e(e'|e) \cdot Q^s \left(s'(\beta') \left| \psi_{\beta'}^{(NFD,b')}(\omega_b)\right.\right)$$
$$\Bigg[\mathcal{W}_{PD}^{b'}(\omega_b) \cdot \Big(1 - \sigma^{(FD,0,0)}(\beta', z', \omega_b', p' = 0)\Big) +$$
$$\Big(1 - \mathcal{W}_{PD}^{b'}(\omega_b)\Big) \cdot \sum_{p'} \mathcal{W}_{p'}^{(R,b')}(\omega_b) \cdot \Big(1 - \sigma^{(FD,0,0)}(\beta', z', \omega_b', p')\Big)\Bigg], \tag{1.14}$$

where the weighting factor $\mathcal{W}_{PD}^{b'}(\omega_b)$ denotes the probability that a household with bank-observable states ω_b and bank loan choice b' chooses payday default $d = PD$ between full repayment and payday default in the current period. It is given by:

$$\mathcal{W}_{PD}^{b'}(\omega_b) = \sum_z Q^z(z) \cdot \frac{\sum_\beta s(\beta) \cdot \sigma_b^{(PD,b')}(\beta, z, \omega_b)}{\sum_{\hat{d} \in \{PD,R\}} \sum_\beta s(\beta) \cdot \sigma_b^{(\hat{d},b')}(\beta, z, \omega_b)}. \tag{1.15}$$

In this case, provided that an individual has chosen to default on her payday loan in the current period, the bank realizes that the only possible payday loan choice in the next period is zero $p' = 0$.

Analogously, $1 - \mathcal{W}_{PD}^{b'}(\omega_b)$ gives the probability of choosing full repayment $d = R$. As banks do not observe p', they must form an expectation over the individual's payday loan choice. Conditional on full repayment, $\mathcal{W}_{p'}^{(R,b')}(\omega_b)$ denotes the probability of a household choosing a certain payday loan p' and is given by:

$$\mathcal{W}_{p'}^{(R,b')}(\omega_b) = \sum_z Q^z(z) \cdot \frac{\sum_\beta s(\beta) \cdot \hat{\sigma}_b^{(R,b',p')}(\beta, z, \omega_b)}{\sum_{\hat{p}'} \sum_\beta s(\beta) \cdot \hat{\sigma}_b^{(R,b',\hat{p}')}(\beta, z, \omega_b)}. \tag{1.16}$$

Payday Lenders

The payday loan pricing schedule is also endogenously determined by the zero-profit condition due to the assumption of perfect competition.[20] For computa-

[20] This assumption can be justified by: (1) there are more payday loan storefronts than McDonald's and Starbucks combined in the U.S (Karger, 2005); (2) Flannery and Samolyk (2005) find that the annual interest rates of payday loans can be accounted for by significant fixed operating costs and higher default premia.

tional tractability, we assume payday lenders use the same type score as banks to infer a household's hidden type.[21] The repayment probability of a contract (R, b', p') for bank-observable states ω_b is thus given by:

$$\mathbb{P}_p^{(R,b',p')}(\omega_b) = \sum_{(\beta',z',e',s')} s(\beta') \cdot Q^z(z') \cdot Q^e(e'|e) \cdot Q^s\left(s'(\beta')|\psi_{\beta'}^{(NFD,b')}(\omega_b)\right)$$
$$\left(1 - \sum_{d' \in \{FD,PD\}} \sum_{b''<0} \sigma^{(d',b'',0)}(\beta', z', \omega_b', p')\right). \quad (1.17)$$

Note that payday lenders have to take into account both formal default FD and payday default PD because payday loans can be discharged in both cases. Moreover, a payday loan can be taken only if a household does not save at banks $b'' < 0$. The payday loan pricing function is thus given by:

$$q_p^{(R,b',p')}(\omega_b) = \rho \cdot \frac{\mathbb{P}_p^{(R,b',p')}(\omega_b)}{1 + r_p}, \quad (1.18)$$

where r_p denotes the operating costs in the payday lending industry.

1.3.4 Evolution of the Household Distribution

The probability for an individual to move from state (β, z, ω_b, p) to $(\beta', z', \omega_b', p')$ is governed by the following mapping:

$$\begin{aligned}
&T^*(\beta', z', \omega_b', p'|\beta, z, \omega_b, p) \\
&= \rho \cdot Q^\beta(\beta'|\beta) \cdot Q^z(z') \cdot Q^e(e'|e) \cdot \sigma^{(d,b',p')}(\beta, z, \omega_b, p) \cdot Q^s\left(s'(\beta')|\psi_{\beta_H'}^{(\tilde{d},b')}(\omega_b)\right) \\
&+ (1-\rho) \cdot G_\beta(\beta') \cdot G_z(z') \cdot G_e(e') \cdot \mathbb{I}_{[b'=0]} \cdot \mathbb{I}_{[s'=G_\beta]} \cdot \mathbb{I}_{[p'=0]}. \quad (1.19)
\end{aligned}$$

The second line describes the transition of surviving households. The third line describes the birth of newborn households. Therefore, the cross-sectional distribution of households μ evolves according to:

$$\mu'(\beta', z', \omega_b', p') = \sum_{(\beta,z,\omega_b,p)} T^*(\beta', z', \omega_b', p'|\beta, z, \omega_b, p) \cdot \mu(\beta, z, \omega_b, p). \quad (1.20)$$

[21] One possible justification is that developing a separate type score technology is too expensive for payday lenders.

1.3.5 Equilibrium

A stationary Recursive Competitive Equilibrium (RCE) is a set of (un)conditional value functions v^* and W^*, bank loan pricing functions q_b^* and repayment probability $\mathbb{P}_b^*$, payday loan pricing functions q_p^* and repayment probability $\mathbb{P}_p^*$, a type scoring function ψ^*, choice probability functions σ^* and $\tilde{\sigma}_b^*$, and a distribution $\overline{\mu}^*$ such that:

1. Household Optimality: $v^{*(d,b',p')}(\beta, z, \omega_b, p)$, $\sigma^{*(d,b',p')}(\beta, z, \omega_b, p)$, and $W^*(\beta, z, \omega_b, p)$ satisfy Equation (1.3), (1.6), and (1.7) for all (β, z, ω_b, p), respectively.

2. Type Score Updating: $\tilde{\sigma}_b^{*(\tilde{d},b')}(\beta, z, \omega_b)$ and $\psi_{\beta'_H}^{*(\tilde{d},b')}(\omega_b)$ satisfy Equation (1.11) and (1.13) for all (β, z, ω_b), respectively.

3. Zero Profits for Banks: $q_b^{*(NFD,b')}(\omega_b)$ and $\mathbb{P}_b^{*(NFD,b')}(\omega_b)$ satisfy Equation (1.9) and (1.14) for all ω_b, respectively.

4. Zero Profits for Payday Lenders: $q_p^{*(R,b',p')}(\omega_b)$ and $\mathbb{P}_p^{*(R,b',p')}(\omega_b)$ satisfy Equation (1.18) and (1.17) for all ω_b, respectively.

5. Stationary Distribution: $\overline{\mu}^*(\beta, z, \omega_b, p)$ solves Equation (1.20).

Note that the banking problem requires knowledge of the cross-sectional distribution of households μ. As a result, all equilibrium objects depend on the distribution, and solving the model numerically becomes a daunting task. To accelerate the computation, we implement the one-loop algorithm where value functions, the type scoring function, pricing schedules, and the distribution are updated simultaneously in each iteration until convergence.[22] Refer to Appendix 1.B for computational details.

1.4 Calibration

The goal of the paper is to explore to what extent the reputation protection channel can explain the payday loan puzzle documented in Agarwal et al. (2009). Given they used a payday loan dataset collected from 2000 to 2004 and to circumvent the effects of the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), we set the baseline calibration year to 2004. The

[22] A similar algorithm is implemented by Hatchondo, Martinez, and Sapriza (2010).

model period is one year. We calibrate the model to the whole U.S. population. Median earnings are set to \$33,176 in 2004 from the Current Population Survey (CPS).[23] Our calibration strategy is threefold: (1) standard parameters are taken from the literature; (2) parameters with a direct empirical counterpart are exogenously calibrated; and (3) the rest are internally calibrated to match targeted data moments.

The persistent and transitory earnings processes are taken from Floden and Lindé (2001). We use their process because they estimated it using wage earnings in the U.S. for the same time period considered in our paper and without life-cycle components. We assume newborn households are endowed with the lowest persistent earnings realization and with transitory earnings drawn randomly from the estimated process. These assumptions imply that newborn households start with low earnings. Following Chatterjee et al. (2020),[24] we set discount factors to 0.886 and 0.915, respectively. The turn-over rates for discount factors are $Q^{\beta}(\beta_H|\beta_L) = 0.013$ and $Q^{\beta}(\beta_L|\beta_H) = 0.011$. These rates imply that households change their types on average every 77 to 91 years. The share of impatient households among newborns is set to 72%. This is consistent with the upward moving of credit ranking along ages observed in data.[25]

We set the CRRA parameter of the utility function to 2, the standard value in the macro literature. The survival probability of households every period is set to 0.975, implying an average working life span of 40 years. The risk-free rate r_f is set to 1.4% and implies an effective interest rate of 4%, consistent with the literature. According to calculations in Albanesi and Nosal (2020), the out-of-pocket filing costs for Chapter 7 before the 2005 bankruptcy reform amounted to approximately \$697, implying $\kappa_{FD} = 0.02$. As Montezemolo and Wolff (2015) pointed out that payday defaults in practice involve two bounced checked fees (one by banks and the other by payday lenders, \$35 each), we set the out-of-pocket filing costs for payday defaults κ_{PD} to 0.002. According to Flannery and Samolyk (2005), the average operating costs (without default losses) per two-week payday loan of size \$230 is around \$19, thus implying

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[23] $\$638$ earnings per week $\times$ 52 weeks $= \$33,176$.

[24] To determine discount factors, Chatterjee et al. (2020) use an affine approximation using the model-generated data to match the means and standard deviations of credit rankings across ages. Our calibrated model can match these moments fairly well.

[25] μ_H denote the share of patient households. Solving $\mu_H = \rho\left[(1 - Q^{\beta}(\beta_L|\beta_H))\mu_H + Q^{\beta}(\beta_H|\beta_L)(1 - \mu_H)\right] + (1 - \rho)G_{\beta_H}$ yields that there are 41% of patient and 59% of impatient households in equilibrium.

Parameter	**Symbol**	**Value**
Persistence of pers. earnings*	ρ_e	0.9136
S.D. to persistent earnings*	σ_e^2	0.0426
S.D. to transitory earnings*	σ_z^2	0.0421
Persistent earnings at birth†	G_e	(1,0,0)
Transitory Earnings at birth†	G_z	(1/3,1/3,1/3)
Low discount factor‡	β_L	0.886
High discount factor‡	β_H	0.915
Transition from low to high‡	$Q^\beta(\beta_H\|\beta_L)$	0.013
Transition from high to low‡	$Q^\beta(\beta_L\|\beta_H)$	0.011
Discount factor at birth‡	G_β	(0.72,0.28)
CRRA§	γ	2
Survival probability¶	ρ	0.975
Risk-free rate‖	r_f	0.014
Formal default cost**	κ_{FD}	0.02
Payday default cost††	κ_{PD}	0.002
Operat. cost for payday lenders‡‡	r_p	1.925
S.D. of extreme value shocks‡	α	0.005

Table 1.1: Exogenously Chosen Parameters

Notes: Targets/Sources: * Floden and Lindé (2001), † Upward earnings profile, ‡ Chatterjee et al. (2020), § Standard, ¶ 40 years, ‖ Effective interest rate = 4%, ** Albanesi and Nosal (2020), †† Montezemolo and Wolff (2015), ‡‡ Flannery and Samolyk (2005).

the annualized operating cost for payday lenders r_p is 1.925. The dispersion parameter of the extreme value distribution is set to 0.005.[26] Table 1.1 provides a summary.

We internally calibrate the stigma costs for formal default κ_{FD} and for payday default κ_{PD} jointly by matching the formal default rate and the conditional payday default rate. The conditional payday default rate refers to the write-off rate among payday loan borrowers in the year after they took out their first payday loans. Results are summarized in Table 1.2. The formal default rate in the data is computed as the total number of non-business Chapter 7 filings

[26]This value is comparable the those used in Chatterjee et al. (2020). To rule out the contribution of extreme value shocks to the payday loan puzzle, we check whether households are making such a seeming pecuniary mistake with higher values. See Section 1.6.1.

Parameter		Value	Target	Data	Model
Formal stigma cost	ξ_{FD}	0.02235	Formal default rate	0.99%	0.99%
Payday stigma cost	ξ_{PD}	0.00702	Payday default rate*	29.7%	29.7%

Table 1.2: Internally Calibrated Parameters

Notes: * The payday default rate denotes the rate conditional on having a payday loan.

from American Bankruptcy Institute (ABI) normalized by the total number of U.S. households in 2004. The conditional payday default rate is taken from Skiba and Tobacman (2018) where they used the same payday loan data as in Agarwal et al. (2009). The formal and payday stigma costs are accordingly set to 0.02235 and 0.00702, respectively.[27]

We also evaluate our model fit on a set of untargeted moments standard in the consumer finance literature. The data and model moments are summarized in Table 1.3.[28] For the fraction of bank loan borrowers in the data, we use the 2004 Survey of Consumer Finances (SCF) and construct a measure of liquid net worth.[29] We then compute the fraction of households with negative liquid net worth. The fraction of payday loan borrowers is computed with the 2010 SCF since information on payday loans was first collected in the 2010 wave. We also use the 2004 SCF to compute the bank debt-to-earnings ratio conditional on borrowing bank loans.[30] Bank debt is measured using the same liquid net worth definition as above. Earnings is computed as wage income measured in the 2004 SCF.

The average interest rate for bank loans is computed as the average credit card interest rate among those having a positive credit card balance in the 2004 SCF, net of the one-year ahead CPI inflation of all urban consumers from the U.S. Bureau of Labor Statistics. We use the payday loan statistics reported in Skiba and Tobacman (2018) to calculate the average interest rate for payday

[27] The values for formal and payday stigma costs correspond to 2.18% and 0.7% of consumption loss on average.

[28] Note that for all SCF-related data moments, we restrict the sample to households with household heads aged between 20 and 60. We do this since our model does not account for retirement or childhood.

[29] We follow Herkenhoff (2019) in constructing this measure of liquid net worth. It is calculated as the difference between a household's liquid assets, such as checking and savings accounts, and credit card debt. We prefer this measure of net worth as we do not explicitly model illiquid assets such as housing in our framework.

[30] We compute the ratio of average debt to average earnings conditional on having bank debts.

Moment (in %)	Data	Model
Households in Debt		
Fraction of bank loan borrowers	20.9	24.26
Fraction of payday loan borrowers	5.61	9.46
Bank debt-to-earnings (cond.)	11.75	6.48
Interest Rate		
Avg. interest rate for bank loans	9.26	8.56
Avg. interest rate for payday loans	447.88	410.85

Table 1.3: Untargeted Moments: Data v.s. Model

loans, net of the one-year ahead CPI inflation.[31]

1.5 Pooling and Cross-Subsidization

In our economy, there is hidden information about a household's type in addition to hidden actions (a household's payday loan choice is unobservable to banks). Because banks cannot observe household types and payday loan choices, they cannot directly design contracts conditioned on these variables.[32] As a result, this limited information structure leads to two-dimensional pooling across household types and payday loans when banks price their loans.[33]

We first illustrate the heterogeneity in behavior and the resulting cross-subsidization of bank loans across types. Figure 1.2 illustrates differences in borrowing and default behavior across impatient and patient households. Figure 1.2a plots the choice likelihood ratio across different bank asset choices b' conditional on a certain state. The choice likelihood ratio denotes the probability of an impatient household saving or borrowing a certain amount relative to a patient one. A high value for the ratio implies that a certain choice is more likely to be taken by an impatient household than a patient one. We can see that impatient households are much more likely to borrow and to borrow more relative to patient households. This is intuitive as households with a lower dis-

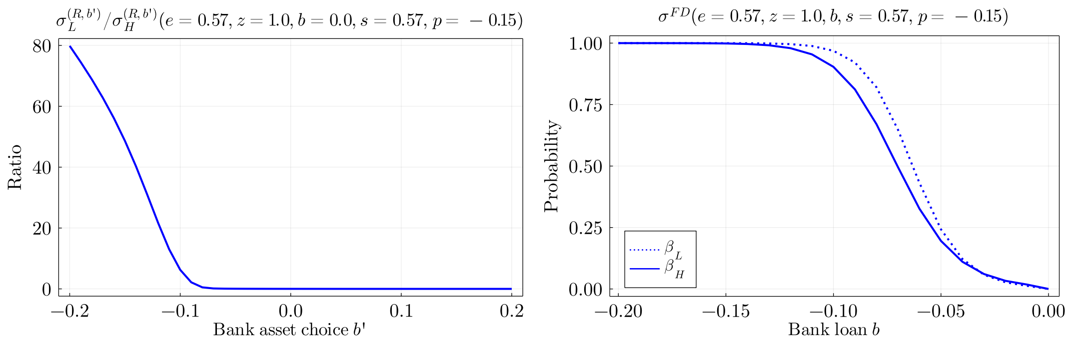
[31] The average bi-weekly payday loan size is \$317.55 with an average interest payment of \$56.4. It implies that $\frac{56.4}{317.55} \times \frac{365}{14} \times \frac{1}{1.03388} \times 100 = 447.88\%$.

[32] As we discussed in Section 1.3.3, banks will instead use type scores and the conditional distribution of payday loans given observed variables.

[33] There is only pooling across types for payday lenders since they can observe a household's payday loan choice. In this section, we will focus on pooling and cross-subsidization in the bank lending market.

Figure 1.2: Borrowing and Default Behavior across Types

(a) Choice Likelihood Ratio (b) Formal Default Probability



Notes: Left figure: The choice likelihood ratio denotes the probability of an impatient household making a certain choice relative to a patient one. A high value for a certain choice b' implies that an impatient household is much more likely to make this choice compared to a patient one. Right figure: The solid line denotes the probability of formal default for a patient household across bank loans b. The dashed line denotes the same probability for an impatient household.

count factor value consumption today more and will therefore tend to borrow more. Figure 1.2b illustrates how the formal default probability varies across levels of bank debt b. The solid line presents the formal default probability for a patient household, while the dashed line shows the probability for an impatient one. It can be seen that the impatient households are more likely to formally default than patient ones across most bank loan positions b. As a consequence, conditional on the same state (and in particular, the same bank loan size), impatient households are riskier borrowers for banks.

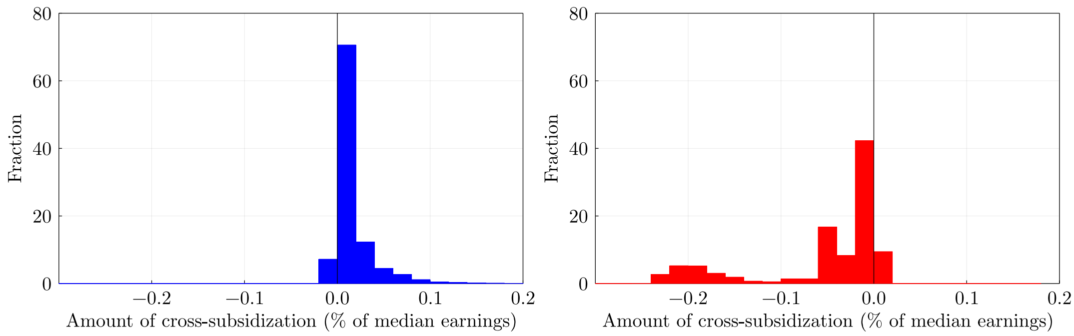
Since banks cannot perfectly infer a household's type, this imperfect distinction across types results in the cross-subsidization of bank loans across types. In Figure 1.3, we plot the distribution of cross-subsidization amounts as a percentage of median earnings for impatient and patient households. Such an amount denotes the extra interest payments that households face in the counterfactual when banks were able to see their types compared to the benchmark, computed as:

$$\left(q^{(NFD,b')} - q_{fair}^{(NFD,b')}(\beta)\right) \cdot b' \times 100, \tag{1.21}$$

where $q_{fair}^{(NFD,b')}(\beta)$ represents the actuarially bank loan price schedule as if banks

Figure 1.3: Cross-Subsidization of Bank Loans across Types

(a) Impatient Households (b) Patient Households



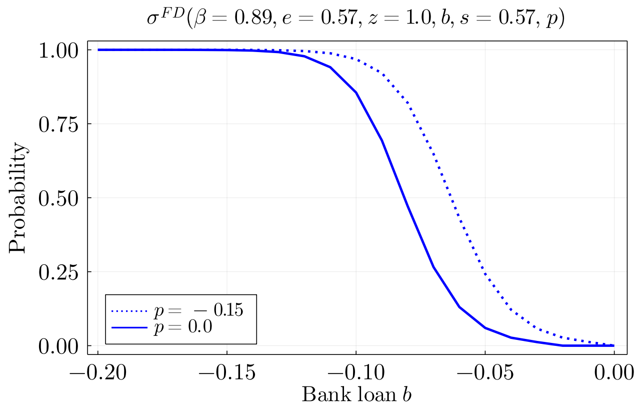
Notes: Cross-subsidization is computed as the difference between actuarially fair interest payments when banks can observe household type and actual interest payments in equilibrium.

knew household types. As shown in Figure 1.3, it is mostly impatient households who are cross-subsidized by patient households. This is due to the fact that the impatient tend to be riskier borrowers as they are more likely to default. In other words, conditional on the same level of bank borrowing, impatient households face lower interest rates on bank loans than actuarially fair rates in our economy.

Moreover, there are also differences in default behavior across payday loan borrowers. Figure 1.4 shows how the formal default probability varies across different levels of bank debt b and households with extra payday debt $p = -0.15$ (dashed line) or not $p = 0$ (solid line). Conditional on the same bank loan position, households with additional payday loan positions are more likely to formally default on both loans. This is straightforward as households with more payday loans have a higher total debt burden and are thus more likely to default. As a result, bank loan borrowers who take out extra payday loans are riskier for banks.

These differences in default behavior lead to cross-subsidization of bank loans across payday and non-payday loan borrowers. Because banks cannot observe payday loan usage by households, borrowers with extra payday loans face the same bank loan pricing schedule as borrowers who do not have payday loans. Conditional on the same level of bank loan, payday loan borrowers tend to have a higher default probability as they have more debt in total. As a result, payday (non-payday) loan borrowers pay lower (higher) rates on bank loans than actuarially fair rates. Figure 1.5 plots the distribution of the cross-subsidization amounts across payday and non-payday loan borrowers. In this

Figure 1.4: Formal Default Probability across Payday Loans



Notes: The solid line depicts the probability for a household with no payday loans to formally default. The dashed line shows the same probability for a household with a payday loan size of 0.15.

case, the amount of cross-subsidization is computed as below.

$$\left(q^{(NFD,b')} - q_{fair}^{(R\vee PD,b',p')}\right) \cdot b' \times 100, \tag{1.22}$$

where $q_{fair}^{(R\vee PD,b',p')}$ represents the actuarially fair bank loan price schedule when banks are able to observe payday loan default and choices.

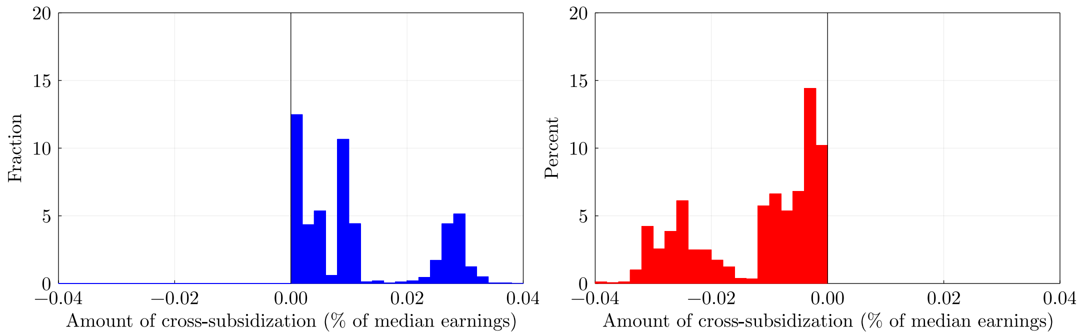
Table 1.4 summarizes the main equilibrium outcomes across types. Compared to patient households, impatient households are more likely to default and borrow, and hold larger debts for both bank and payday loans. This leads to overall higher borrowing costs for the impatient even though they are partially cross-subsidized by patient households as shown in Figure 1.3.

1.6 The Payday Loan Puzzle

In this section, we first illustrate how we identify the payday loan puzzle in our model. Then, we examine to what extent our model can account for the puzzle in the data. In addition, we quantify the type score gains and interest costs from using payday loans and investigate under what circumstances households use payday loans to protect their type scores in our model.

Figure 1.5: Cross-Subsidization of Bank Loans across (Non-)Payday Loan Borrowers

(a) Payday Loan Borrowers (b) Non-Payday Loan Borrowers



Notes: Cross-subsidization is computed as the difference between actuarially fair interest payments when banks can observe payday loan usage and actual interest payments in equilibrium.

1.6.1 Identification of the Payday Loan Puzzle

In our model, we identify the households who make seeming pecuniary mistakes that are consistent with the payday loan puzzle in the following way: for each possible state (β, z, ω_b, p), we identify those feasible borrowing choices with repayment $(R, b' < 0, p' < 0) \in \mathcal{F}(z, \omega_b, p)$ that involve a payday loan where the same total amount of borrowing $\hat{b}' = b' + p'$ could have been achieved at lower borrowing costs using bank loans only. That is:

$$\left| q_b^{(NFD,b')}(\omega_b) \cdot b' + q_p^{(R,b',p')}(\omega_b) \cdot p' \right| < \left| q_b^{(NFD,\hat{b}')}(\omega_b) \cdot \hat{b}' \right|. \tag{1.23}$$

The borrowing choices that fulfil the above condition are the choices that we classify as the payday loan puzzle. Let the set of these choices be called $\mathcal{P}(\beta, z, \omega_b, p)$.[34]

[34] Recall that, in a model with utility shocks, any feasible action will be chosen with positive probability (not just the choice with the highest value). As a result, households might take up payday loans because mainly of such shocks. To control for this nuisance, we additionally check whether households are conscious of making this decision with higher values. To be specific, for each state (β, z, ω_b, p), the feasible borrowing choices with repayment $(R, b' < 0, p' < 0) \in \mathcal{F}(z, \omega_b, p)$ where the value of borrowing a certain amount is higher when using payday loans compared to only using bank loans. That is:

$$v^{(R,b',p')}(\beta, z, \omega_b, p) > v^{(R,\hat{b}',p=0)}(\beta, z, \omega_b, p). \tag{1.24}$$

Hence, there exists the general dependency of $\mathcal{P}(\cdot)$ on β. In fact, Condition (1.24) is pretty weak as almost all borrowing choices using both loans are fulfilled.

Moment (in %)	Aggregate	Impatient	Patient
Default			
Formal default rate	0.99	1.27	0.57
Payday default rate (cond.)	29.7	30.6	27.9
Households in debt			
Fraction of bank loan borrowers	24.26	27.5	19.55
Fraction of payday loan borrowers	9.46	10.7	7.65
Fraction of both loan borrowers	8.42	9.54	6.77
Bank debt-to-earnings (cond.)	6.48	6.54	6.36
Payday debt-to-earnings (cond.)	1.91	2.00	1.73
Interest rate			
Avg. interest rate for bank loans	8.56	8.79	8.06
Avg. interest rate for payday loans	410.85	433.89	362.74

Table 1.4: Equilibrium across Types

Notes: The payday default rate and the payday debt-to-earnings ratio are conditional on having any payday loans. The bank debt-to-earnings ratio is conditional on having any bank loans.

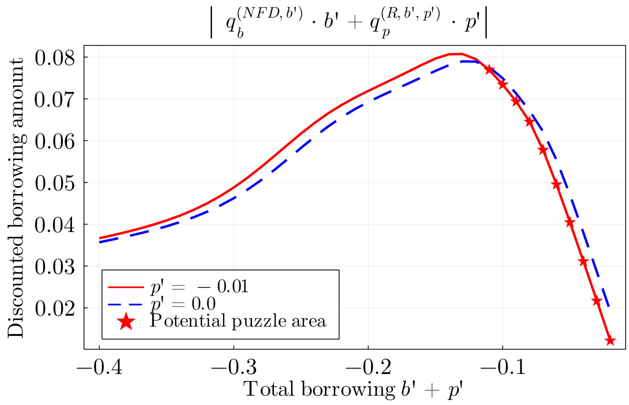
To illustrate where the region with payday loan puzzle can happen, Condition (1.23) is visualized in Figure 1.6 where we plot the discounted borrowing amounts across total borrowing conditional on a certain state. The solid line denotes the discounted borrowing amounts involving a given payday loan $p' = -0.01$ and the dashed line denotes the discounted borrowing amounts without any payday loan $p' = 0$. The region of choices satisfying the condition is marked by asterisks and labeled as "Potential Puzzle Area."

Recall that Agarwal et al. (2009) use a matched dataset of credit cards and payday loans to identify the payday loan puzzle. We accordingly define the rate of puzzle occurrence as the fraction of households that make a choice which would be classified as the payday loan puzzle relative to all households that borrow using both loans. More specifically, the rate of puzzle occurrence in the model is calculated as follows:

$$\frac{\sum_{\beta,z,\omega_b,p} \mu(\beta,z,\omega_b,p) \cdot \sum_{(d,b',p')\in\mathcal{P}(\beta,z,\omega_b,p)} \sigma^{(d,b',p')}(\beta,z,\omega_b,p)}{\sum_{\beta,z,\omega_b,p} \mu(\beta,z,\omega_b,p) \cdot \sum_{(d,b',p')\in\mathcal{F}_{both}(z,\omega_b,p)} \sigma^{(d,b',p')}(\beta,z,\omega_b,p)}, \tag{1.25}$$

where the numerator represents the unconditional fraction of households mak-

Figure 1.6: Identification of the Payday Loan Puzzle



Notes: The discounted borrowing amount is computed as the borrowing amount multiplied by the associated discount borrowing price.

ing the puzzling behavior; the denominator denotes the fraction of households borrowing using both types of loans; and the feasible set of borrowings choices using both loans $\mathcal{F}_{both}(z, \omega_b, p)$ is defined as:

$$\mathcal{F}_{both}(z, \omega_b, p) \equiv \{(d, b', p') | (d = R, b' < 0, p' < 0) \in \mathcal{F}(z, \omega_b, p)\} . \tag{1.26}$$

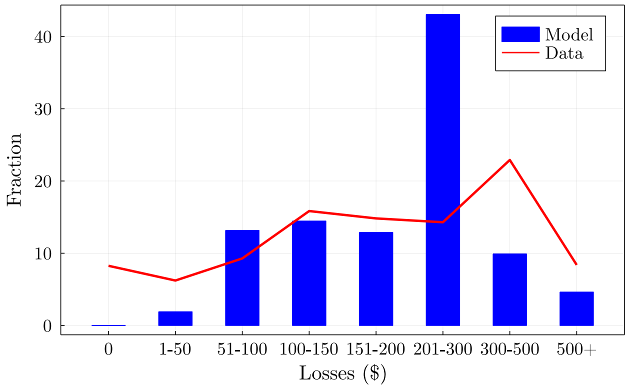
Our model can account for a significant fraction of the puzzling households who take out expensive payday loans with cheaper borrowing alternatives available, identified in the data. In the model, the rate of puzzle occurrence is around 26.44%.[35] Agarwal et al. (2009) empirically identify a rate of around two-thirds in their dataset. Thus, our model can account for around 40% of the payday loan puzzle found in the data.[36]

Our model can also match the magnitude of monetary costs from the payday loan puzzle. Recall that these costs denote the amounts which the puzzling payday loan borrowers could have saved if they had first exhausted their credit cards. Figure 1.7 shows the distribution of the corresponding annual monetary costs per household in both data (solid line) and our calibrated model (bar chart). We can see that in our model most monetary costs have the same

[35] The rate of puzzle occurrence among impatient households is 25.55% and among patient ones is 28.31%. The unconditional fraction of puzzling households is 2.28% in aggregate, 1.5% among impatient households, and 0.78% among patient ones.

[36] Note that cheaper costs for payday default than formal default are not the main factor with which our calibrated model can generate the payday loan puzzle. Refer to Appendix 1.C for details.

Figure 1.7: Histogram of Monetary Costs of Payday Loan Puzzle



Notes: The data series is from Agarwal et al. (2009). The monetary costs are the amounts which households could have saved if they first exhausted their credit cards before taking out payday loans over one year.

magnitude ranging from \$0 to \$500 as in the data.[37] Moreover, our calibrated model predicts average annual monetary costs of \$230, which is in line with the average amount of around \$200 reported in Agarwal et al. (2009). Essentially, these costs represent the value of reputation protection in our model.

1.6.2 The Reputation Protection Channel

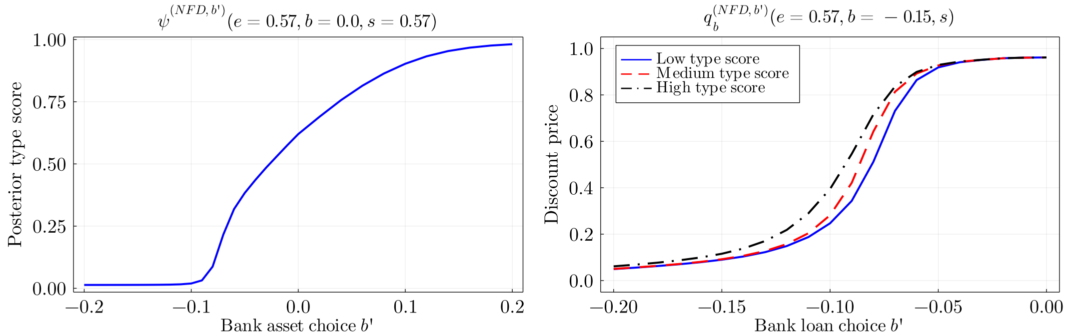
We now explore the reputation protection hypothesis quantitatively in our model. In our model, borrowing larger bank loans leads to a lower type score. In addition, households with lower type scores face higher bank interest rates. Hence, households have an incentive to borrow using payday loans instead of bank loans in order to avoid a negative impact on their type scores, thus giving them access to cheaper bank credit in the future.

Figures 1.2 and 1.8 illustrate how this mechanism works. Figures 1.2a and 1.8a show the effects of bank loan choices on type scores. In Figure 1.2a, we can see how impatient households are more likely to borrow and to borrow more relative to patient households. Figure 1.8a shows the type score updating function and depicts how a household's type score is updated conditional on different bank asset choices b'. We can see that taking out a larger bank loan (or saving less) leads to a worse type score update because banks realize that the

[37] We can even match the distribution of these costs rather well, apart from the bins of \$201-\$300 and \$300-\$500.

Figure 1.8: Reputation Protection Incentive

(a) Type Score Update (b) Bank Loan Discounted Price Schedule



Notes: Left figure: The type score update is plotted across different bank asset choices b' conditional on a certain state (e, b, s). A new type score of 1.0 means that a household is assessed to be patient with probability one. Right figure: The discounted price schedule for bank loans is shown across different bank loan choices b' conditional on a certain state (e, b, s). The discount price is inversely related to the interest rate. The solid/dashed/dash-dotted lines denote the schedules offered to households with low/medium/high type scores.

impatient are more likely to borrow larger amounts. Figures 1.2b and 1.8b show how a lower type score leads to higher interest rates. Figure 1.2b illustrated how impatient households are more likely to formally default than patient ones across different levels of debt. Figure 1.8b illustrates the bank loan discounted price schedules for households with low (solid line), medium (dashed line), and high type scores (dash-dotted line). Banks will charge households with lower type scores lower discounted prices (higher interest rates) in order to be compensated for the additional default risk.

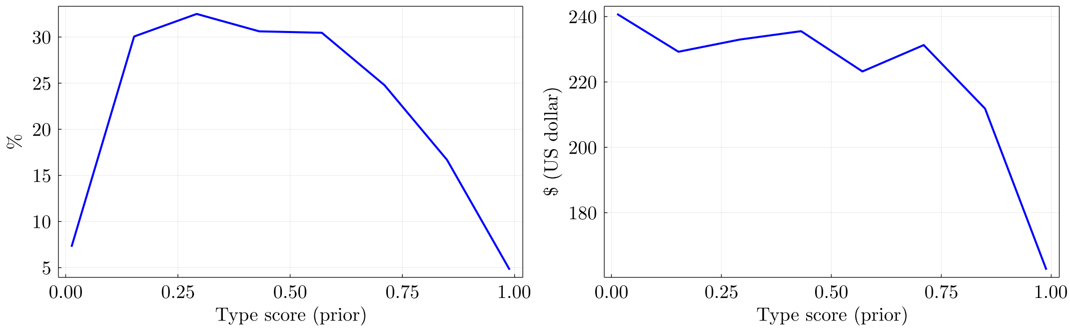
Figure 1.9 looks at the trade-off between type score protection and monetary costs for using payday loans among the payday loan borrowers with cheaper credit available. Figure 1.9a illustrates the relative gain in posterior type scores from using payday loans compared to borrowing the same amount using only bank loans across different prior type scores.[38] There exists significant prior-dependent heterogeneity.[39] In particular, the gain is over 30% for those who

[38] To be precise, the relative gain in posteriors for given bank-observable states ω_b is computed as: $\left(\psi^{(NFD,b')}_{\beta'_H}(\omega_b) - \psi^{(NFD,\hat{b}')}_{\beta'_H}(\omega_b)\right) \Big/ \psi^{(NFD,\hat{b}')}_{\beta'_H}(\omega_b) \times 100$ where $\psi^{(NFD,b')}_{\beta'_H}(\omega_b)$ and $\psi^{(NFD,\hat{b}')}_{\beta'_H}$ denote the updated type scores for borrowing a bank loan of b' and for borrowing a mixture of bank and payday loans $\hat{b}' = b' + p'$.

[39] The hump shape results from the fact that prior dominates in the type score updating at both ends (i.e., when banks believe a household to be a certain type).

Figure 1.9: Cost-Benefit Analysis among Seemingly Puzzling Households

(a) Posterior Type Score Gain (b) Monetary Costs



Notes: Left figure: The type score gain is computed by comparing the posterior type score of using payday loans relative to using only banks loans for the same borrowing amount, conditional on a prior type score, and expressed in percentage points. Right figure: The monetary costs denote the extra interest payments incurred using payday loans compared to using bank loans for the same borrowing amount across prior type scores.

have lower medium prior type scores. Figure 1.9b calculates the monetary costs in U.S. dollars across prior type scores.[40] These costs refer to the extra interest expenses incurred by using payday loans compared to using bank loans for the same borrowing amount. Such pecuniary costs are significant and vary across prior type scores. For example, households with the lowest possible type score are willing to pay an additional $240 in payday loan interest fees to achieve higher type scores. On average, these puzzling households, i.e., taking out payday loans while having cheaper borrowing alternatives available, are willing to pay an additional $230 in interest payments on payday loans for an increase in type scores by 23%. On average, a 1% increase in type scores, in turn, leads to a lower borrowing interest rate by 16% in the future bank lending market.[41]

1.6.3 Profile of Puzzling Households

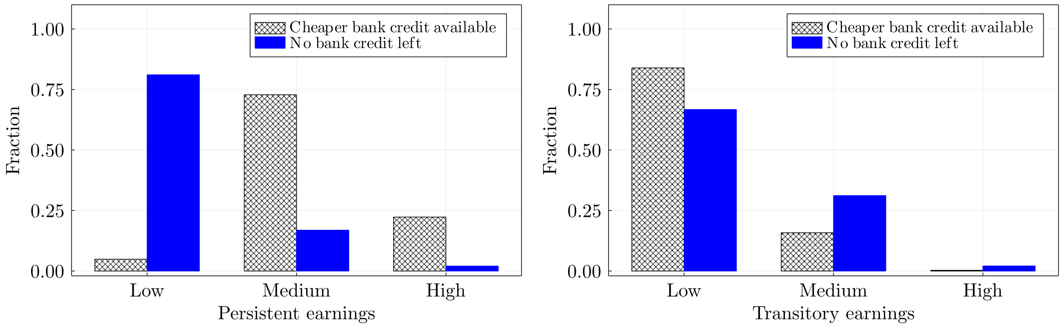
In the previous subsection, we illustrated how using payday instead of bank loans can lead to significant type score gains at the cost of substantially higher interest costs in the short run. Better type scores thus lead to better access to credit markets in the long run. In this subsection, we further investigate when

[40] If we express these monetary costs in percentage points relative to the counterfactual, the resulting plot also exhibits a hump-shaped pattern.

[41] See Appendix 1.D for more general results.

Figure 1.10: Earnings Distribution among Both Loan Borrowers

(a) Persistent Earnings (b) Transitory Earnings



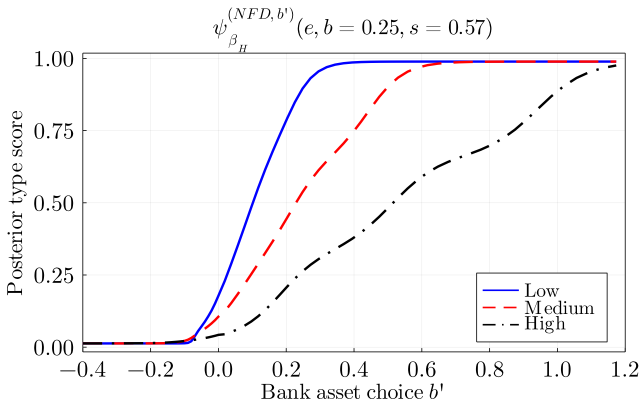
Notes: These figures show the distribution of payday loan borrowers who have exhausted their cheaper bank loans or not across persistent (left figure) and transitory (right figure) earnings. "Cheaper bank credit available" refers to the households who borrow using both loans even though they have not exhausted cheaper bank credit (see conditions 1.23 and 1.24). ""No bank credit left" refers to the households who borrow using both loans but have exhausted cheaper bank credit.

households engage in this seemingly puzzling behavior in our calibrated model.

Figure 1.10 plots the distribution of both loan borrowers across persistent earnings (Figure 1.10a) and transitory earnings (Figure 1.10b), conditional on whether the cheaper bank credit has been exhausted or not yet. We can see that, compared to the borrowers who have exhausted their cheaper bank credit (solid bar chart), borrowers who have not exhausted their cheaper bank credit yet (argyle bar chart) tend to have higher persistent but lower transitory earnings. In particular, households take out payday loans before exhausting cheaper bank loans when they have medium to high persistent earnings but low transitory earnings in our model. This observation indicates that these puzzling households use payday loans to smooth out the shortfall in transitory earnings without significantly damaging their type scores (such a trade-off has been explained in Figure 1.9).

However, why are the households with this earnings profile especially incentivized to borrow using payday loans instead of cheaper bank loans? Recall that banks can observe persistent earnings but not transitory earnings. Therefore, taking out bank loans to smooth out a negative transitory earnings shock while having high persistent earnings will lead to a downgraded type score. This explanation is illustrated in Figure 1.11 which shows the type score updating

Figure 1.11: Type Score Updating across Persistent Earnings



Notes: This figure plots the updated type score for different bank asset choices b' across persistent earnings for a certain state. The solid/dashed/dash-dotted lines denote the type score updating function with low/medium/high persistent earnings.

across bank asset choices for different persistent earnings. Conditional on the same bank asset choice b', a household with low persistent earnings (solid line) will receive a higher type score update than a household with medium (dashed line) or high (dash-dotted line) persistent earnings. The intuition is as follows. Borrowing a larger bank loan is more indicative of impatience (low discount factor) when having high compared to low persistent earnings because banks think those with higher persistent earnings are not supposed to borrow that much. Instead, by complementing bank loans with payday loans, which are unobservable to banks, households can reduce the negative impact on their type scores while still being able to smooth out transitory earnings shocks.

1.7 Policy Experiments

In this section, we consider two different policy experiments that are highly relevant in the consumer credit market: policies curtailing (or outright banning) payday loans and bankruptcy law regulation.

1.7.1 Payday Loan Regulation

Payday loans have been a subject of intensive public debate. Opponents of payday loans have long argued that payday lenders prey on poor households and should be banned. Advocates emphasized the role of payday loans in smoothing consumption.

We contribute to this debate by investigating the welfare implications of limiting access to payday loans through quantity caps or an outright ban on payday loans in our model. Table 1.5 summarizes the key results of these policy counterfactuals where we report the key moments and welfare outcomes measured in consumption equivalent variation (CEV) units relative to the benchmark in percentage points.[42] The column "Benchmark" describes the calibrated model as presented in the previous sections. The column "Quantity Cap" denotes the counterfactual where the possible payday loan choices are limited to a size of \$300 which is the smallest possible payday loan in the benchmark economy.[43] The column "Full Ban" describes the counterfactual where payday loans become unavailable in the economy.

Compared to the benchmark, a quantity cap leads to fewer payday loan borrowers as there are less payday loan choices available. Conditional on borrowing payday loans, payday debt-to-earnings ratio also drops. It then leads to a decrease in the (unconditional) payday default rate to 2.2% since it is less advantageous to default on smaller payday loans.[44] The unconditional payday default rate also drops mechanically as there are less payday loan borrowers. In addition, the conditional effective default rate on payday loans, which is defined as the fraction of households defaulting on payday loans through either formal or payday default conditional on have any payday loans, also decreases from around 34.68% in the benchmark to 31.24%. Accordingly, the average payday interest rate decreases. The formal default rate also decreases slightly and as such there is no substitution from payday default to formal default as a consequence of the payday loan cap. This in turn gives rise to a mild decrease in average bank interest rate. Surprisingly, the *extensive margin* of bank loan borrowing also decreases: the fraction of bank loan borrowers drops slightly. The lack of an increase in the extensive margin of bank loan borrowers is explained by the fact that most payday loan borrowers were already borrowing bank loans in the benchmark economy. Instead, limiting the size of payday loans leads to an increase in the *intensive margin* of bank loan usage: conditional on borrow-

[42] Note that households barely change their types even though types are assumed to be stochastic. Given our calibration, the average life expectancy of 40 years is two times smaller than the average type-switching period of around 80 years. Refer to Section 1.4 for details.

[43] \$300 is the average payday loan size in the data.

[44] The monetary filing cost stays the same as in the benchmark economy.

Variables (in %)	Bench.	Quantity Cap	Full Ban
Default			
Formal default rate	0.99	0.96	0.89
Payday default rate	2.81	2.19	–
Eff. payday default rate (cond.)	34.68	31.24	–
Households in debt			
Fraction of bank loan borrowers	24.26	24.06	23.15
Fraction of payday loan borrowers	9.46	8.22	–
Fraction of both loan borrowers	8.42	7.36	–
Bank debt-to-earnings (cond.)	6.48	6.61	6.84
Payday debt-to-earnings (cond.)	1.91	1.40	–
Interest rate			
Avg. interest rate for bank loans	8.56	8.53	8.46
Avg. interest rate for payday loans	410.85	341.88	–
Welfare			
Welfare – aggregate	–	−0.0012	−0.0291
Welfare – impatient households	–	−0.0029	−0.0331
Welfare – patient households	–	0.0013	−0.0233
Cross-Sub. of bank loans			
Avg. cross-sub. across types	–	-10.5	-15.1
Avg. cross-sub. payday borrowers	–	-21.0	-100.0

Table 1.5: Policy Counterfactual: Restricting Payday Loan Size

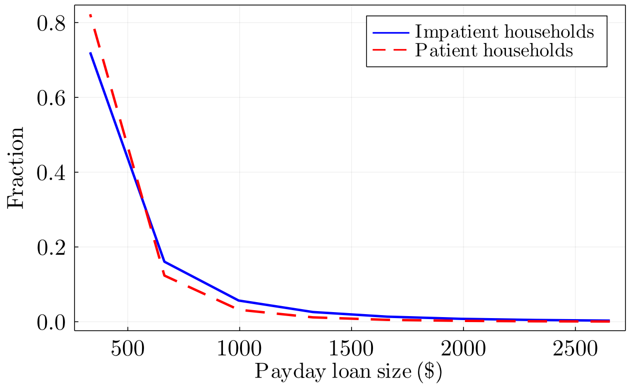
Notes: Bench. denotes the benchmark case. The conditional effective payday default rate is defined as the fraction of households choosing to default on payday loans through either formal or payday default, conditional on having any payday loans. The bank debt-to-earnings ratio is conditional on having any bank loans. The payday debt-to-earnings ratio is conditional on having any payday loans. Welfare is measured in CEV units relative to the benchmark in percentage points. Cross-sub. stands for cross-subsidization. The average cross-subsidization amount of bank loans is computed as in Section 1.5 but expressed in percentage changes relative to the benchmark.

ing, bank debt-to-earnings ratio rises. This is because borrowers now partially substitute bank loans for payday loans. In the full ban counterfactual, all of these changes are magnified.

The overall welfare effects of both policy counterfactuals are negative.[45]

[45] Note that our framework measures the lower bound of the welfare effects of type scores since, in practice, individuals with higher credit scores have better mortgage terms and

Figure 1.12: Distribution of Payday Loan Size across Types



Notes: This figure illustrates the distribution of payday loan borrowers across different payday loan amounts for impatient households (solid line) and patient households (dashed line).

More interestingly, the welfare implications of experiments are heterogenous across household types. Impatient households lose in terms of welfare whenever the payday loan market becomes more constrained. In contrast, patient households have higher welfare in the quantity cap counterfactual but lower welfare in the full ban counterfactual compared to the benchmark economy. The reasons for the declines in welfare for impatient households are intuitive. First, impatient households are more likely to borrow larger payday loans in the benchmark economy and are thus more affected by the quantity cap or ban, as shown in Figure 1.12. Second, imposing a payday loan quantity cap or banning payday loans also reduces the informational asymmetry regarding payday loan usage in the bank market. In turn, this reduction allows banks to better assess a household's type and reduces pooling across types in the bank loan market. As a result, there is less cross-subsidization of impatient by patient households as we can see in Table 1.5. This decrease in cross-subsidization explains the increase in welfare for patient households but the decrease in welfare for impatient households in the quantity cap counterfactual.

So what explains the decrease in welfare for patient households when payday loans are fully banned? The answer is that there is a second factor at play apart from cross-subsidization: insurance. Constraining payday loan choices makes it harder for everyone in the economy, including patient households, to insure against idiosyncratic shocks. When payday loans are quantity capped but still

labor market outcomes, both of which are not considered in our model.

available in the economy, the reduction in cross-subsidization outweighs this reduced insurance for patient households. But patient households do depend on payday loans to smooth shocks, for example in order to reduce the negative effect on type scores of a transitory earnings shock as discussed in Section 1.6. In the full ban economy, this loss of insurance outweighs the gain from reduced cross-subsidization for patient households. This result implies that in our model fully banning payday loans makes both types of households worse off.

1.7.2 Bankruptcy Regulation

Another approach to regulation in the consumer finance market taken by policy makers is through bankruptcy laws. The most notable overhaul of bankruptcy regulation in recent years is the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) in 2005. Among other changes, this legislation increased the total out-of-pocket filing cost for Chapter 7 filings by around 35% (Albanesi and Nosal, 2020). To examine the effect of such an increase in monetary filing cost in our model, we simulate a counterfactual where the formal filing cost is increased by 35% ($1.35 \times \kappa_{FD}$). In addition, we also consider the policy counterfactual where the payday filing cost rises by the same magnitude ($1.35 \times \kappa_{PD}$) to assess the implication of stricter regulation on payday lending. The key results of these policy counterfactuals are summarized in Table 1.6. The column "$1.35 \times \kappa_{FD}$" denotes the counterfactual where the formal filing cost is increased by 35%. The column "$1.35 \times \kappa_{PD}$" describes the counterfactual where the payday filing cost is increased by 35%.

Focusing first on the case where the formal filing cost is increased, we can observe that this change leads to a significant decrease in the formal default rate. This is caused by substitution from formal default to payday default as the (unconditional) payday default rate rises. The drop in the formal default rate leads to a decrease in the average bank interest rate as banks require a lower default premium on their loans. This, in turn, makes borrowing using bank loans cheaper and increases bank loan borrowing both in terms of the extensive (fraction of loan borrowers) and intensive (debt-to-earnings) margins. Interestingly, the increase in bank loan borrowing is not accompanied by a decrease in payday loan borrowing. Rather payday loan usage also increases, leading to an overall higher level of debt in the economy. This is because the conditional effective default rate on payday loans actually drops from 34.68%

Variables (in %)	**Bench.**	**$1.35 \times \kappa_{FD}$**	**$1.35 \times \kappa_{PD}$**
Default			
Formal default rate	0.99	0.84	0.99
Payday default rate	2.81	3.03	2.60
Eff. payday default rate (cond.)	34.68	33.59	33.78
Households in debt			
Fraction of bank loan borrowers	24.26	26.35	24.21
Fraction of payday loan borrowers	9.46	10.11	9.07
Bank debt-to-earnings (cond.)	6.48	7.56	6.48
Interest rate			
Avg. interest rate for bank loans	8.56	7.51	8.56
Avg. interest rate for payday loans	410.85	395.01	398.23
Welfare			
Welfare – aggregate	–	0.1236	−0.0032
Welfare – impatient households	–	0.1404	−0.0036
Welfare – patient households	–	0.0991	−0.0026

Table 1.6: Policy Counterfactual: Higher Filing Costs

Notes: Bench. denotes the benchmark case. $1.35 \times \kappa_{FD}$ denotes the counterfactual where the formal filing cost is increased by 35%. $1.35 \times \kappa_{PD}$ the counterfactual where the payday filing cost is increased by 35%. The conditional effective payday default rate is defined as the fraction of households choosing to default on payday loans through either formal or payday default, conditional on having any payday loans. The bank debt-to-earnings ratio is conditional on having any bank loans. The payday debt-to-earnings ratio is conditional on having any payday loans. Welfare is measured in CEV units relative to the benchmark in percentage points.

in the benchmark to 33.59%, thus implying cheaper borrowing costs for payday loans.

Continuing to the case where the filing cost for payday default is increased, the payday default rate drops mechanically as it becomes more expensive to default on payday loans. This is associated with a lower average payday loan interest rate. We can also see that the fraction of payday loan borrowers drops even though payday interest rates have fallen. The reason is that in our economy households often default on payday loans. The utility of payday loan borrowers decreases as the increase in payday default costs outweighs the lower payday interest costs. All bank-related variables remain roughly unchanged.

The welfare implications of increasing the filing costs for either formal or payday default are the opposite: an increase in formal default costs leads to a welfare gain for both types of households, whereas an increase in payday default costs leads to a welfare loss. On the one hand, a stricter bankruptcy regime through higher default costs leads to lower interest rates, making borrowing cheaper. On the other hand, a stricter regime makes it more costly to default in response to bad shocks.[46] In our model, it is cheaper to borrow using bank loans compared to payday loans. At the same time, it is less costly to default on payday than bank loans as both the reputational and monetary filing costs are lower. Thus, households prefer to borrow using bank loans and to default on their payday loans first.[47] Increased formal default costs exactly allow households to take out bank loans at even lower interest rates, which explains the welfare gain in this counterfactual. In contrast, increased payday default costs make it harder for households to default on their payday loans, which explains the welfare loss in this case.

1.8 Conclusion

One puzzle in the consumer finance literature is the so-called "Payday Loan Puzzle": households use expensive payday loans even when they still have cheaper alternatives, such as credit cards. We propose a new rational explanation of this behavior: these households use payday loans to protect their credit scores since payday lenders do not report to credit bureaus. To investigate this hypothesis, we build a two-asset Huggett-type model with two types of consumer default as well as asymmetric information and hidden actions. Households can be of one of two types: patient with a high discount factor or impatient with a low discount factor. This household type is unobservable to lenders. In order to form an expectation of a household's type, lenders compute an individual-specific type score based on one's credit history. In addition, a household's payday loan choice is also not observable to banks. This information structure then endogenously creates an incentive for households to use payday loans instead of cheaper bank loans to protect their type scores.

Our model can successfully replicate the payday loan puzzle by matching

[46] This explanation refers to the insurance-efficiency trade-off of a bankruptcy regime between *smoothing over time* and *smoothing across states* (Zame, 1993).
[47] This argument is also valid across types. As shown in Table 1.4, the average payday interest rates are far higher than the ones for bank loans for both types.

both the fraction of households that show behavior consistent with the payday loan puzzle as well as the magnitude of the monetary costs. Furthermore, we illustrate how the reputation protection channel leads to the emergence of the payday loan puzzle in our framework. We then conduct a series of policy experiments. We show that restricting the size of payday loans benefits patient households at the expense of impatient ones, while a full ban on payday loans results in a welfare loss for both types of households. In addition, we also show that increasing the costs of defaulting on payday loans is welfare-reducing, whereas increasing the costs of formal default is beneficial in terms of welfare. These results imply that current regulatory efforts in the U.S. to curtail or even ban the payday loan sectors may potentially be harmful to households.

In the future, one might consider a policy experiment where banks can observe payday loan usage by requiring payday lenders to report. This alternative specification would allow us to more cleanly separate the effect of policy on pooling across types versus pooling across payday loan borrowers, thus guiding regulation of the payday lending industry.

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Appendix

1.A Assignment of Posterior Type Score

As the updated type score ψ may not lie on the original type score grid, it is randomly assigned to one of the two nearest grid points $s'_i(\beta')$ and $s'_j(\beta')$ for all β' with $s'_i(\beta') \leq \psi^{(\tilde{d},b')}_{\beta'_H} \leq s'_j(\beta')$, and assign probability $\chi(\beta'|\psi)$ to $s'_i(\beta')$ and $1 - \chi(\beta'|\psi)$ to $s'_j(\beta')$, where

$$\chi(\beta'|\psi) = \frac{s'_j(\beta') - \psi^{(\tilde{d},b')}_{\beta'_H}(\omega_b)}{s'_j(\beta') - s'_i(\beta')}, \quad \forall \beta'. \tag{1.27}$$

For all s' such that $s'(\beta') \in \{s'_i(\beta'), s'_j(\beta')\}$ for all β', the probability of receiving score s' in the next period is thus equal to

$$Q^s(s'|\psi) = \prod_{s'(\beta')=s'_i(\beta')} \chi(\beta'|\psi) \cdot \prod_{s'(\beta')=s'_j(\beta')} (1 - \chi(\beta'|\psi)). \tag{1.28}$$

For all other s', $Q^s(s'|\psi) = 0$.

1.B Computation

1.B.1 Grid Specifications

We discretize the persistent and transitory earnings processes, each with three points, using Adda and Cooper (2003) and uniform distribution, respectively. We choose the lower bounds for bank and payday loans to ensure that the endogenous borrowing limits are included. Check Appendix 1.D for the pricing schedules in equilibrium. We then consider an equally-spaced grid of 40 points for bank loans and an exponentially-spaced grid of 150 points for bank savings. More importantly, the grid for payday loans is designed with the same spacing

Variable	Symbol	# Points	Range
Persistent earnings	e	3	$\{0.57, 1.00, 1.74\}$
Transitory earnings	z	3	$\{0.78, 1.00, 1.29\}$
Bank assets	b	191	$[-0.40, 15.00]$
Payday loans	p	16	$[-0.15, 0.00]$
Type scores	s	8	$[0.013, 0.989]$

Table 1.B.1: Grids Used for Model Computation

as bank loans to properly compare the borrowing choices between bank and payday loans when identifying the payday loan puzzle.

1.B.2 One-Loop Algorithm

1. Set parameters and tolerances for convergence.

2. Create grids for (β, z, ω_b, p) with lengths $(n_\beta, n_z, n_\omega, n_p)$ where $n_\omega = n_e \times n_b \times n_s$.

3. Initialize algorithm with starting guesses:

   (a) $W(:,:,:,:,s,:) = W^{FI}$ for all s where W^{FI} denotes the unconditional value function under full information.

   (b) $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b) = s \cdot Q^\beta(\beta_H|\beta_H) + (1-s) \cdot Q^\beta(\beta_H|\beta_L)$ for all ω_b and $(\tilde{d}, b')$.

      i. $s'_i = \max\left\{s \in \mathcal{S} | s \leq \psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)\right\}$ and $s'_j = \min\left\{s \in \mathcal{S} | s \geq \psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)\right\}$.

      ii. $Q^s\left(s'_i(\beta_H)|\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)\right) = \frac{s'_j - \psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)}{s'_j - s'_i}$ and $Q^s\left(s'_j(\beta_H)|\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)\right) = \frac{\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b) - s'_i}{s'_j - s'_i}$.

   (c) $q_b^{(NFD,b')}(:,b,s) = q_b^{FI}$ for all b, s where q_b^{FI} denotes the bank loan price function under full information.

   (d) $q_p^{(R,b',p')}(:,b,s) = q_p^{FI}$ for all b, s where q_p^{FI} denotes the payday loan price function under full information.

   (e) $\mu(:,:,:,:,s,:) = \frac{1}{n_s} \times \mu^{FI}$ for all s where μ^{FI} denotes the cross-sectional distribution of households under full information.

4. Begin the one-loop algorithm:

   (a) Solve for new W_1 taking as given W_0.

      i. Find set of feasible actions (d, b', p') using (1.4).

      ii. For each (β, z, ω_b, p), compute the value $v^{(d,b',p')}(\beta, z, \omega_b, p)$ for each feasible action (d, b', p') according to (1.3).

      iii. Compute new W_1 using (1.7).

   (b) Compute $\sigma^{(d,b',p')}(\beta, z, \omega_b, p)$ according to (1.6).

   (c) Compute new equilibrium functions.

      i. On bank side:

         A. Compute $\tilde{\sigma}_b^{(\tilde{d},b')}(\beta, z, \omega_b)$ using (1.10) and (1.11).

         B. Then $\psi_{\beta'_H}^{(\tilde{d},b')}(\omega_b)$ using (1.13).

         C. Then $\chi(\beta'|\psi)$ using (1.27) for all ψ from previous step.

         D. Then $Q^s(s'|\psi)$ using (1.28) for all ψ from previously.

         E. Then $\mathbb{P}_b^{(NFD,b')}(\omega_b)$ using (1.14).

         F. Finally $q_b^{(NFD,b')}(\omega_b)$ using (1.9).

      ii. On payday lender side:

         A. Compute $\mathbb{P}_p^{(R,b',p')}(\omega_b)$ using (1.17).

         B. Then $q_p^{(R,b',p')}(\omega_b)$ using (1.18).

   (d) Compute stationary distribution μ_1 using (1.20).

   (e) Assess convergence of W, ψ, q_b, q_p, and μ.

      i. If achieved, continue to the next step.

      ii. Otherwise, update the initialization of the targeted objects with relaxation and return to step (a).

5. Compute moments.

1.C Robustness Check: Same Default Costs

Given that payday default costs are lower than those for formal default, households might take out payday loans because of the better across-state insurance through defaulting on payday loans at lower costs. To argue that this filing channel is not the primary driver for our calibrated framework to generate the

Moment (in %)	Benchmark	Same Default Costs
Default		
Formal default rate	0.99	5.21
Payday default rate (cond.)	29.7	22.0
Households in debt		
Fraction of bank loan borrowers	24.26	16.40
Fraction of payday loan borrowers	9.46	9.24
Fraction of both loan borrowers	8.42	8.42
Interest rate		
Ave. interest rate for bank loans	8.56	59.38
Ave. interest rate for payday loans	410.85	1435.12
Payday loan puzzle		
Rate of puzzle occurrence	26.44	51.38

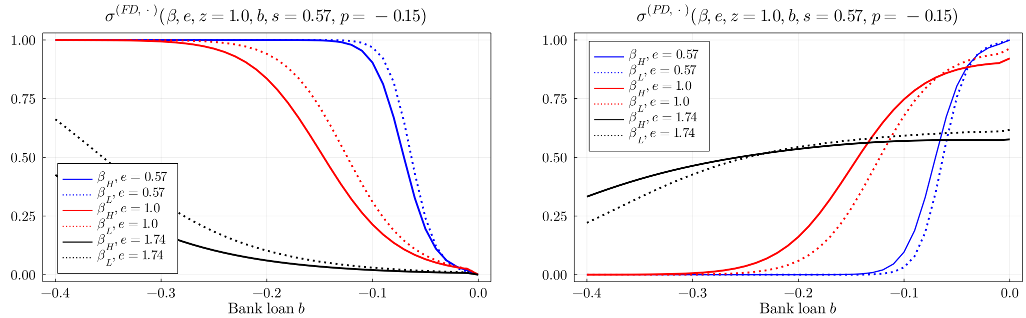
Table 1.C.1: Counterfactual: Same Default Costs

payday loan puzzle, we consider a counterfactual where we set the filing and stigma costs for formal default to those for payday default. That is, defaulting on bank loans is as cheap as on payday loans, either pecuniarily or mentally. Important moments and the rate of payday loan puzzle occurrence are reported in Table 1.C.1, along with the benchmark results.

We can see that, compared to the benchmark, households substitute formal default for payday default as it becomes cheaper to execute formal default. A higher formal default rate increases the interest costs for bank and payday loans since households can discharge both loans with formal default. Higher borrowing costs result in drops in the fractions of either loan borrowers at the extensive margin. More importantly, the rate of puzzle occurrence is almost two times larger than the one in the benchmark. The increase can be explained by the fact that payday loans are very costly in the counterfactual. As a result, Condition (1.23) is much more likely to be satisfied, conditional on borrowing using both loans. This result suggests that cheaper costs for payday default than formal default are not the main driving force for our calibrated model to generate the payday loan puzzle.

Figure 1.D.1: Default Probabilities

(a) Formal Default (b) Payday Default

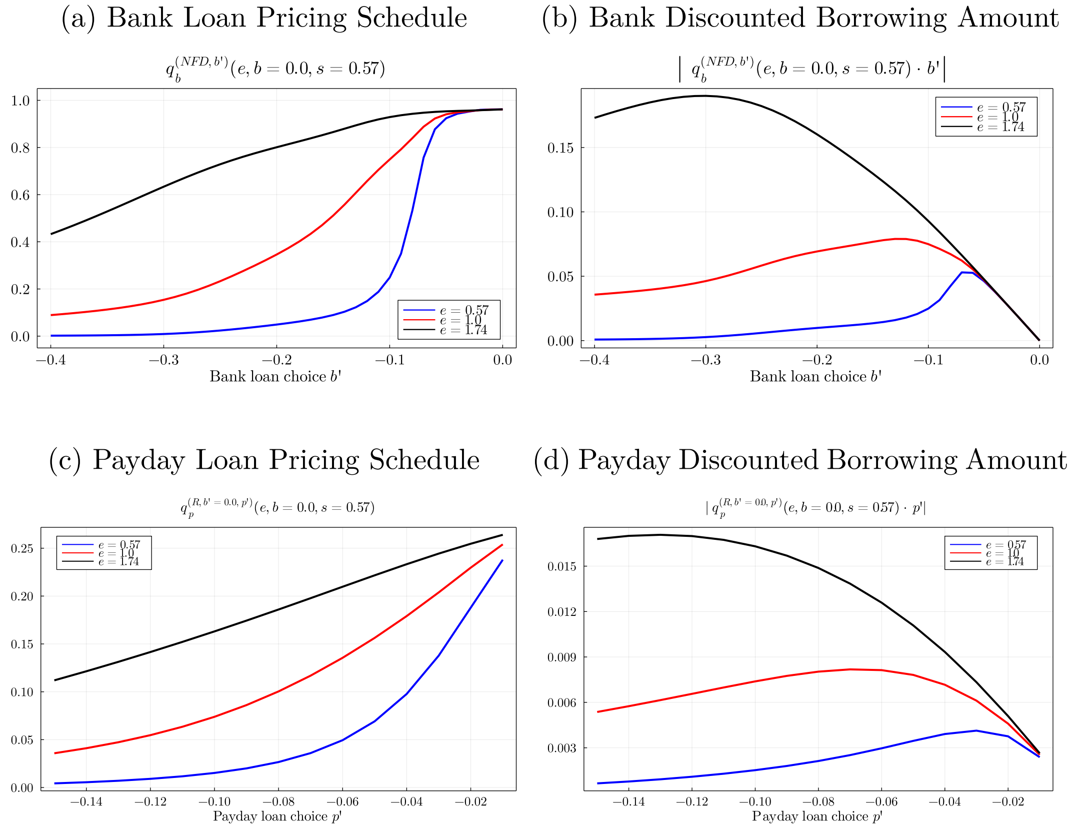


1.D General Results

Figure 1.D.1 depicts how default probabilities vary across (persistent) earnings e and types β. The left-hand side shows how the probability of a household choosing formal default increases as its debt burden grows (b becomes more negative). Households with lower earnings start to formally default at lower debt burdens compared to households with higher earnings. Furthermore, more impatient households (β_L) also start to formally default at smaller debt levels. In contrast, as can be seen on the right-hand side the probability of payday default decreases as the debt burden grows. This is due to the switching from payday to formal default: As bank loans increase households switch from payday defaulting on their payday loans only to formally defaulting on all debt in order to discharge their larger bank loans. We can see in Figure 1.D.1b that this switching starts earlier at lower debt levels for households with less income (black line starts dropping at lower b) and for households that are more impatient (dashed lines drop more quickly than solid lines). This happens because low types are less concerned about the long-term reputational damage from formal default.

The pricing schedules and the risky borrowing limits of bank and payday loans across earnings in the model are depicted in Figure 1.D.2. These results are quite standard in consumer default models. The intuition is clear: On the one hand, borrowing more this period will lead to a higher default probability next period c.p. as the gain from defaulting is larger. As a result we can see in Figure 1.D.2a that borrowing more (more negative b') leads to lower prices/higher interest rates. Furthermore, an individual with lower persistent

Figure 1.D.2: Pricing Schedule and Discounted Borrowing Amount

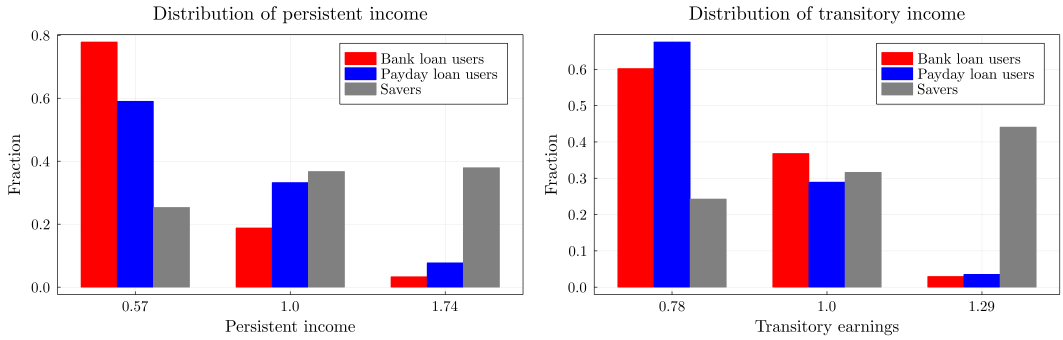


earnings e will face lower prices compared to one with higher e c.p. due to the difference in default probability in the following period. Similarly, the payday loan pricing schedules and the risky borrowing limits across earnings in the model are in the bottom panel. These results are similar to those of bank loans. The significant disparity in levels across bank and payday loans results from the fact that payday lenders have higher operating costs than banks (i,e, higher lending costs).

Figure 1.D.3 illustrates what kind of household in our economy saves or borrows. On the left, Figure 1.D.3a shows the distribution of savers and borrowers across *persistent* income. Unsurprisingly, savers in our economy tend to have higher (persistent) income compared to borrowers. We can also see that households who use bank loans (either only bank loans or together with payday loans) are overwhelmingly poor (the red bars). Perhaps more interestingly, payday loan borrowers, while still being poor compared to savers, tend to

Figure 1.D.3: Earnings Distribution among Borrowers and Savers

(a) Persistent Earnings (b) Transitory Earnings



have higher persistent income than bank loan borrowers. On the right, Figure 1.D.3b shows the distribution of households across *transitory* income. Compared to Figure 1.D.3a it can be seen that payday loan borrowers tend to have lower transitory income than bank loan borrowers. These two figures suggest that the two types of loans are used to smooth different types of income shocks in our model: households use bank loans to smooth persistent income shocks whereas payday loans are used to smooth transitory shocks. This makes sense: Payday loans are more expensive than bank loans and are much more costly to smooth a persistent negative income shock. On the other hand, using payday loans does not (directly) affect your type score. As a result, it can make sense to smooth transitory income shocks using payday loans in order avoid long-term reputational damage to a household.

Figure 1.D.4a plots the type score distributions among borrowers and savers. We can see that savers in our economy tend to have higher type scores compared to either bank or payday loan borrowers. Interestingly, payday loan borrowers have slightly lower type scores compared to bank loan borrowers. Figure 1.D.4b instead depicts the type score distribution among puzzle and non-puzzle users. We can see that the prior type score distributions of both users are skewed to the right. More importantly, puzzle borrowers, those who take out payday loans before exhausting cheaper bank credit, tend to have lower prior type scores in contrast to non-puzzle borrowers, those who take out payday loans without cheaper bank credit available. This is because the reputation gain (the interest costs) are higher (lower) for households with lower type scores (see Figure 1.9).

Figure 1.D.5 plots the variation in updated type scores relative to priors

Figure 1.D.4: Type Score Distribution

(a) Borrowers vs. Savers (b) Puzzle vs. Non-Puzzle Users

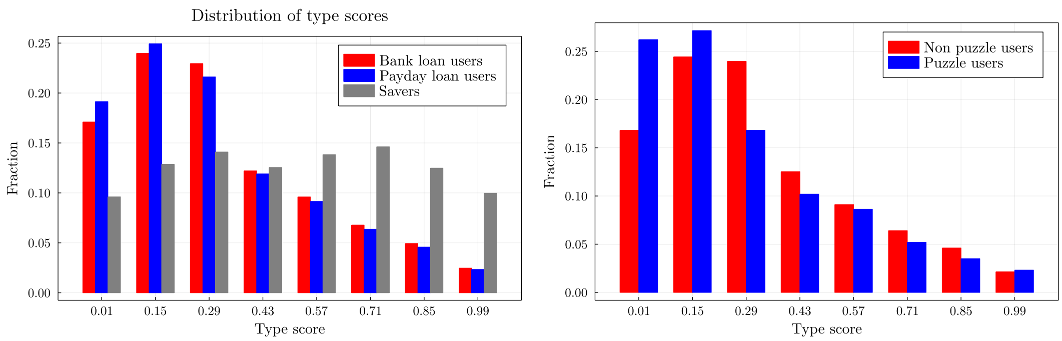
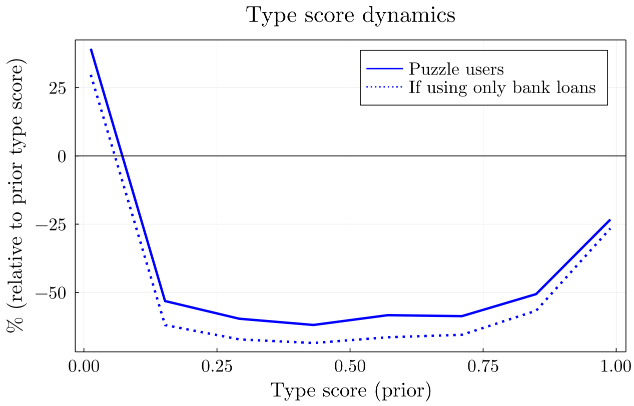


Figure 1.D.5: Posterior Type Score Dynamic

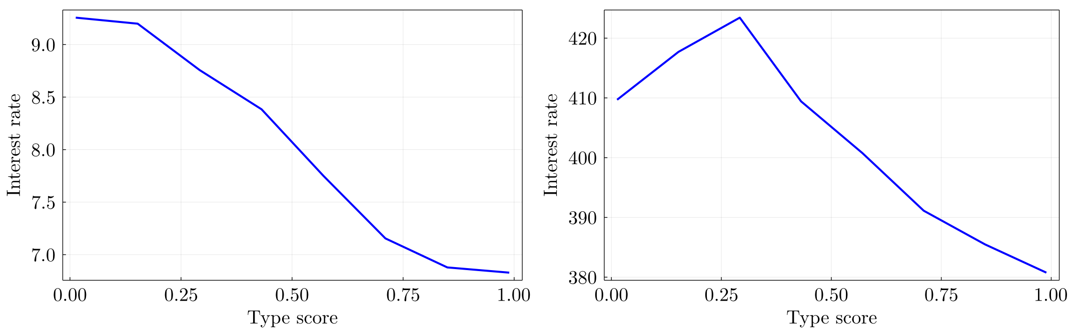


among puzzle users in percentage (solid line) compared to the counterfactual when they were to borrow the same amount using only bank loans (dotted line). Borrowing only banks loans results in overall lower posterior type scores across all priors, compared to borrowing a mixture of bank and payday loans. This is intuitive as banks can observe only bank loans. Borrowing more bank loans thus indicates more impatience.

Figure 1.D.6 plots the average interest rates for bank loans (Figure 1.D.6a) and payday loans (Figure 1.D.6b) across type scores. We can see that higher type scores lead to lower interest rates in both bank and payday lending markets. In particular, the difference in bank loan interest rates between households with the lowest and highest type scores is over 2%. On the other hand, the interest rate difference in the payday lending market can be up to 90%.

Figure 1.D.6: Average Interest Rates for Bank and Payday Loans across Type Scores

(a) Bank Loans (b) Payday Loans



Chapter 2

The Role of Marital Status for the Evaluation of Bankruptcy Regimes

2.1 Introduction

Household bankruptcy rates in the United States differ significantly across marital status. This fact has been documented by many empirical studies. Sullivan, Warren, and Westbrook (2000) show that single individuals are over-represented among bankruptcy filers while married are under-represented in the U.S. in 1991.[1] In particular, divorced individuals made up 23% of all bankruptcy filers while only representing 9.7% of the U.S. population at that time. More recently, Fisher (2019) documents that being divorced is highly correlated with bankruptcy conditional on a host of socio-economic characteristics, such as age, race, education, income, employment, home-ownership, etc. In a similar vein, Agarwal, Chomsisengphet, and Liu (2011) estimate that married credit card holders are 32% less likely to declare bankruptcy compared to non-married ones, again conditional on a large range of socio-economic controls. Fay, Hurst, and White (2002) highlight the importance of divorce events as their results suggest that the probability of bankruptcy increases by 86% in the year following a divorce.

However, until now the quantitative consumer default literature has exclusively employed models that do not differentiate between single and couple

[1] See Figure 6.1 in Sullivan et al. (2000).

households.[2] All households are modeled as a single entity. Prior work, such as Livshits, MacGee, and Tertilt (2007), emphasized the importance of income and expense risk for the welfare evaluation of bankruptcy regimes. Couple households differ from single households in these aspects: First, couples have potentially access to two earners. A spouse can adjust his/her labor supply in response to the partner's earnings shocks, the *intra-HH insurance channel*. Previous literature has emphasized this channel both empirically (see e.g. Blundell, Pistaferri, and Preston (2008)) as well as structurally (see e.g. Ortigueira and Siassi (2013)). Thus, couples face different income risk than singles. Second, couples by nature face different expense risk compared to singles. Couples consist of two individuals who both can suffer expense shocks. In addition, couples are also at risk of divorce, an event that is costly and often goes hand in hand with bankruptcy as mentioned earlier. Finally, couples also benefit from economies of scale in consumption whereas singles do not.[3]

My contribution in this paper is building a consumer default model that explicitly differentiates between single and couple households for the first time and examining the implications for the welfare evaluation of bankruptcy regimes. I build upon the lifecycle Huggett-type model with consumer default in Livshits et al. (2007). Individuals derive utility from consumption and leisure. They are subject to wage and expense shocks. In response to these shocks individuals choose how much to work. Households also choose how much to save or borrow as well as whether to repay their loans or to default. Default is costly and a fraction of the filing household's wage is garnished. Furthermore, couples can become divorced. Financial services are provided by competitive financial intermediaries. These intermediaries price loans according to the individual default risk of the borrower. There is no asymmetric information in my model.

I calibrate my model to the U.S. population in 2019. Standard parameters are taken from the literature. Other parameters are exogenously calibrated to data whenever possible. I pay particular attention to the estimation of expense shocks. Previous literature has shown that medical expenses are a main component of these shocks and that they are key for welfare implications.[4] I estimate out-of-pocket medical expenses separately for single and married individuals

[2] In the following, I will use the terms couple and married household interchangeably.

[3] Clearly, there are other dimensions of heterogeneity between couples and singles, such as childbirth and childcare. As my paper is the first that models couples and singles explicitly in a consumer default setting, I abstract from these differences in this paper as a first step.

[4] For example, Livshits et al. (2007).

using data from the Medical Expenditure Panel Survey (MEPS) for 2018 and 2019.[5] The remaining parameters, including the discount factor, the utility weight on consumption, the wage garnishment rate, and the annual transaction cost of lending are internally calibrated to match the several aggregate data moments. I also evaluate my model on a set of untargeted moments.

Using my calibrated model I first compute ex-ante welfare of newborns across different garnishment rates for single and couple households. There exists a trade-off when considering the optimal garnishment rate: On the one hand, a more lenient bankruptcy regime in the form of a lower garnishment rate allows households to default more cheaply in response to adverse shocks. On the other hand, a stricter bankruptcy regime reduces default rates, resulting in lower default premia in equilibrium and as a result cheaper loans for households.[6] I find that single and married households prefer different degrees of bankruptcy leniency. In my model, couples prefer a more lenient regime than singles. I then decompose which sources of heterogeneity between singles and couples drive this finding. I find that differences on the income side of households cause couples to prefer a **stricter** regime than singles. This is because couples have access to the intra-household insurance channel: Spouses can adjust their own labor supply in response to their partners' wage shocks. This additional source of insurance for couples means that they have less need for the insurance provided by bankruptcy. However, this channel is outweighed by the additional risk faced by couples through divorce and because couples are hit more often by expense shocks (due to consisting of two individuals instead of one). These two factors make couples value bankruptcy more than singles. The net effect is that couples prefer a more lenient regime. Overall, my results suggest that marital status is an important source of heterogeneity when evaluating the welfare implications of different bankruptcy regimes.

The remainder of the paper is structured as follows: Section 2.2 gives an overview of the related literature. In Section 2.3 I summarize how household bankruptcy works in the U.S. with a focus on differences between single and married filers. Section 2.4 presents the model framework. In Section 2.5 I

[5] Out-of-pocket, not total, medical expenses are the relevant type of expense for this model. This is because out-of-pocket expenses have to be paid by the individuals themselves and are thus relevant to the bankruptcy decision. Expenses paid by insurance do not affect a household's bankruptcy choice.

[6] In the literature, the first channel is referred to as smoothing consumption *over states*. The second one is described as smoothing *over time*.

detail the calibration of my model and how I estimate medical expense shocks from data. Section 2.6 presents the welfare result of my baseline model as well as a decomposition of the different channels at work. Section 2.7 contains a robustness check. Section 2.8 concludes with some potential further avenues for research.

2.2 Related Literature

In this section I discuss the literature most closely related to my paper. I begin with papers from the consumer default literature. Afterwards, I summarize some papers which emphasize the importance of modeling singles and couples separately. Two important ingredients in my model are the intra-household insurance channel and expense shocks. I conclude this section by presenting a brief overview of some papers that have looked at these two elements.

My paper is closely related to the structural literature on consumer default. Livshits et al. (2007) is one of the workhorse models in this literature. The authors analyze two different bankruptcy regimes: "fresh start (FS)" and "no fresh start (NFS)". In a FS economy households are allowed to discharge debt by defaulting. In contrast, in a NFS economy debt cannot be discharged but must instead be repaid under a repayment plan. They build a heterogeneous agent lifecycle model and examine the welfare consequences of the two regimes. They find that the nature of expense and income uncertainty is crucial for the welfare assessment of the two regimes. Livshits, MacGee, and Tertilt (2010) build on the same model to investigate the rise in consumer bankruptcy filings between 1970 to 2002. They argue that the most important drivers behind this development are lower lending transaction costs and decreasing costs of bankruptcy. Chatterjee, Corbae, Nakajima, and Ríos-Rull (2007), another workhorse model in this literature, build a consumer default model with infinitely-lived households. They study the welfare implications of a means test introduced in the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005.[7] The authors show that this policy change leads to welfare gains in their model. Herkenhoff (2019) examines the relationship between changes in consumer credit access and business cycles. To do so, he builds a consumer default model with a labor

[7] The means test is a test that Chapter 7 bankruptcy applicants have to pass before filing. It prevents households with income above certain thresholds to file.

market subject to search and matching frictions. Chatterjee, Corbae, Dempsey, and Ríos-Rull (2020) build a consumer default model with asymmetric information between lenders and borrowers. In their model lenders compute a credit score for each borrower to better assess their creditworthiness. A paper that models endogenous labor supply in a consumer default framework like mine is Exler (2019). In contrast to my paper, none of the studies above model single and couple households separately.

My paper is also related to a growing literature emphasizing the importance of explicitly modeling singles and couples for understanding household behavior and for analyzing policy implications. De Nardi, French, Jones, and McGee (2021) try to understand the savings behavior of retired households using a structural approach. In order to do so, they show that it is important to model marital status along with medical expenses and bequest motives. Borella, De Nardi, and Yang (2021) look at how the dependence of taxes and retirement benefits on marital status affects female labor supply. Their results suggest that an elimination of marriage-related provisions would result in increased labor force participation of women and lead to large welfare gains for most households. Guner, Kaygusuz, and Ventura (2012) study the effects of two tax reforms while explicitly modeling couples: a proportional income tax and a reform allowing separate filing for married individuals. They illustrate that both reforms lead to a large increase in the labor supply of married females. Bacher (2021) examines how marital status affects the investment choices of households. She finds that divorce risk lowers the demand for illiquid assets. Failure to explicitly account for marital status thus results in overestimation of the attractiveness of housing and housing-related policies. In contrast to these studies, my paper is the first to examine the importance of distinguishing between single and couple households in a consumer default setting.

One important mechanism in my model is the intra-household insurance channel. There exists a large literature that examines how spousal labor supply acts as insurance against risk. On the one hand, empirical studies have investigated this channel. Blundell et al. (2008) use the PSID to study changes in income and consumption inequality. Among other results, they document that family labor supply plays an important role for insuring against permanent income shocks. Also using the PSID, Shore (2010) examines the cyclical properties of the intra-household insurance channel. On the other hand, there exists a structural literature which studies this mechanism. Kotlikoff and Spivak (1981) is an early paper that studies the insurance provided by a family. Attanasio, Low, and Sánchez-Marcos (2005) use a lifecycle model with a unitary family to study the role of spousal labor supply as insurance against earnings risk. They show that the welfare cost of increased uncertainty is higher if female labor supply cannot be adjusted. Ortigueira and Siassi (2013) use an Aiyagari-Huggett setup with couples in order to quantify the effects of this channel on household behavior. In their model couples suffer a much weaker consumption drop upon unemployment relative to single individuals.[8] Compared to these papers, I embed the intra-household insurance channel in a consumer default framework and investigate its effects on bankruptcy behavior.

Another important ingredient in my model are expense shocks. There is a sizeable literature that tries to quantify medical expenses and look at their effect on different household dynamics. French and Jones (2004) use data from the Health and Retirement Survey and the Assets and Health Dynamics of the Oldest Old to estimate a stochastic process for health care costs of old people. Hubbard, Skinner, and Zeldes (1994) build a lifecycle model including uncertain longevity and medical expenses. They show that these features help match wealth and consumption dynamics in the U.S. Palumbo (1999) builds a structural model in which elderly individuals suffer from medical expense shocks. He demonstrates that uncertain medical expenses help explain the dissaving behavior of retired people. De Nardi, French, Jones, McGee, and Rodgers (2020) estimate medical expenses for retired individuals using the Health and Retirement Study. They document that medical expenses in addition to bequests can explain asset changes around an individual's death. In contrast to these studies, I focus on medical expenses for working age people and on the effects of these expenses on household default behavior. Another paper in the consumer default literature that highlights the importance of expense shocks is Livshits et al. (2007). They find that expense uncertainty is crucial for the comparison of different bankruptcy regimes and show that with larger expense uncertainty households prefer a more lenient regime.

[8] Their results also suggest that wealth-poor households rely more on spousal labor supply as an insurance mechanism.

2.3 Institutional Details

Households in the United States have access to two types of bankruptcy: Chapter 7 and Chapter 13. Chapter 7 bankruptcy (also called liquidation) allows households to discharge their unsecured debt.[9] In return, assets above a certain exemption level are liquidated to repay the creditors. However, not everyone is allowed to file for Chapter 7. The Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 introduced a so-called means test. This means test prevents individuals above certain income thresholds from filing for Chapter 7.[10] Under Chapter 13 bankruptcy (also called reorganization) debtors can propose a repayment plan. Compared to Chapter 7, Chapter 13 allows debtors to keep their assets in general. As Chapter 7 bankruptcy is the most prevalent form of household bankruptcy, I follow most of the consumer default literature in focusing on this type in my paper.

Compared to filing for Chapter 7 as a single household, filing as a married couple is more complex. When a married couple decides to default, it has three choices: (1) File jointly for bankruptcy, (2) one spouse files whereas the other does not, and (3) both spouses file but separately. When a couple files jointly, the debts of both spouses get discharged. In return, assets of both spouses are eligible to be liquidated. Depending on the state, a joint filing may allow a couple to double certain asset exemptions and thus let couples keep more of their assets.[11] Filing jointly also has the advantage of lower per capita legal fees, as lawyer and court costs only have to be paid once.

When one spouse chooses to file for bankruptcy and the other does not, which debts are discharged and which assets can be liquidated depends on state laws. In general, U.S. states can be divided into those that follow "common law" and those that follow "community property law".[12] In common law states assets acquired during marriage belong to the acquiring spouse only (unless the asset was acquired in the names of both). In these states only the filer's own debts are discharged. The other spouse remains liable for any of her/his own debt as

[9] Some notable exceptions include student loans, childcare, and alimony.

[10] For more details, see e.g. `https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-7-bankruptcy-basics`.

[11] For an overview of the exemption regulations in different U.S. states, see e.g. `https://www.nolo.com/legal-encyclopedia/bankruptcy-exemptions-state`.

[12] Most U.S. states follow common law. Those that follow community property law are Arizona, California, Idaho, Louisiana, Nevada, New Mexico, Texas, Washington, and Wisconsin. Many European countries also follow community property law.

well as for debts that belong to both spouses. Assets that belong to the non-filing spouse cannot be liquidated however, only assets that belong to the filer. This is in contrast to community property states where assets purchased during marriage belong to both spouses by default. Certain community property states allow the discharge of joint debts even if only one spouse files. At the same time, in some community property states joint assets may be liquidated even if one spouse did not file. As my framework only allows joint assets for couples, I see my model as representative of community property states.

2.4 The Model

Each model period lasts three years. My setup uses a lifecycle model where households start life at age 20. Households are identical ex-ante. They live for 16 periods and die at age 68 with probability one. Households maximize their discounted lifetime utility from consumption and leisure.

There are two different household types: singles and couples. Singles can be either female or male. Couples consist of one female and one male individual. They always start life and die together. There is no marriage in the model. Singles always stay single. Couples are subject to an exogenous, random divorce shock. The probability of this divorce shock is the same for all couples. After divorce, there is no possibility of re-marriage. Couples are modeled in a unitary framework and they jointly decide on their actions.

Individuals in the economy can choose the time they spend on working. They are subject to idiosyncratic uncertainty including wage shocks as well as expense shocks. The wage process follows a persistent autoregressive process and differs between female and male individuals. Expense shocks are i.i.d. and vary between singles and couples as well as across age. In the following sections, I suppress the dependence of the expense shock on marital status and age for better readability. In addition, households are subject to a deterministic lifecycle productivity profile. There is no aggregate uncertainty.

Households can save or borrow to smooth consumption. Asset markets are incomplete. Households only have access to one-period non-contingent bonds. Couples have access to a joint asset.[13] Importantly, households may declare bankruptcy in order to insure themselves against shocks. In case of default, a

[13]For tractability I assume that spouses in a couple cannot have separate asset holdings.

fraction of the household's wage is garnished.[14] In return all debt and expense shocks are discharged. A household may also default when it has savings but is subject to an expense shock. When this happens, all savings are lost. Couples are only allowed to jointly file for bankruptcy.[15]

I assume that all individuals are born with zero assets and do not face an expense shock in their first period of life. There is however heterogeneity regarding the starting wage. For simplicity, I assume that it is drawn from a uniform distribution over all possible wage realizations.

Loans and saving services are extended by a perfectly competitive financial intermediary sector. This sector takes as given the exogenous risk-free rate. Loans are priced such that in expectation the financial intermediary makes zero profit on every loan it extends. Households take as given this loan pricing schedule. There is no asymmetric information.

The timing within each period is as follows: First, households realize their wage and expense shocks. In response to these shocks, they choose how much to work and whether to default or not. If a household does not default, it also chooses how much to save or borrow. Couples realize their divorce shock at the beginning of each period. If a couple becomes divorced, the two individuals separate and make their own choices as divorced individuals for the period. Assets are split equally upon divorce.

In the rest of this section, I formally introduce the problem of households in Section 2.4.1. Section 2.4.2 describes the problem of the financial intermediaries. Finally, in Section 2.4.3 I define the equilibrium.

2.4.1 Households

In this section I describe the problem of households. First, I start with the problem facing single households. Afterwards, I lay out the problem of couples before turning to the divorced' problem.

[14]In practice, Chapter 7 bankruptcy does not entail wage garnishments. However, one may interpret the garnishment as an honest effort of the borrower to repay his debts as required by U.S. bankruptcy law under the good faith requirement.

[15]As couples only have access to a joint asset, it does not make sense to model separate bankruptcy filings for them within this model setup.

Singles

Each period, singles choose whether to default or repay:[16]

$$V_{S,g,j}(a, z_g, \kappa) = \max\{V^R_{S,g,j}(a, z_g, \kappa), V^D_{S,g,j}(z_g)\} \tag{2.1}$$

where $V_{S,g,j}(a, z, \kappa)$ is the value function of a single (S), with gender g and age j. The value depends on the individual's asset position a, wage shock z_g drawn from a persistent AR(1) process, and i.i.d. expense shock κ. $a > 0$ denotes savings, whereas $a < 0$ denotes borrowing. $V^R_{S,g,j}$ denotes the value of repayment, while $V^D_{S,g,j}$ is the value of defaulting.[17]

The repayment value function for singles is given by:

$$V^R_{S,g,j}(a, z_g, \kappa) = \max_{(a',n)} u\,(c, l) + \beta \cdot \mathbb{E}_{z'_g,\kappa'}\left\{V_{S,g,j+1}(a', z'_g, \kappa')\right\} \tag{2.2}$$

s.t.

$$c + q^{(a')}_{S,g,j}(z_g) \cdot a' \leq e_j \cdot z_g \cdot n + a - \kappa \tag{2.3}$$

$$l = T - n \tag{2.4}$$

In Equation (2.2) singles choose their next period asset position a' and labor supply n. They maximize utility from consumption c and leisure l and the expected next period value discounted by β. The expectation is taken over next period's realization of the wage shock z'_g and expense shock κ'.

Equation (2.3) shows the budget constraint. The resources available to the household are shown on the right hand side. Income is determined by a lifecycle productivity component e_j, the persistent wage shock z_g (which can differ across gender g), and the labor choice n. a is the asset position that individuals entered the period with. Available resources are reduced by the expense shock κ. On the left hand side, the individual can choose consumption c and next period's asset position a'. $q^{(a')}_{S,g,j}(z_g)$ denotes the discount pricing schedule for loans. Note that the price for a loan depends on its size a' as individuals are more likely to default on a larger loan ceteris paribus. The price also depends on marital status S, gender g, age j, and productivity z_g as all these variables influence the

[16] Note again that I suppress the dependence of the expense shock κ on marital status and age.

[17] The value of defaulting does not depend on assets a or expense shock κ. This is because in case of default, all assets and expense shocks are discharged.

repayment probability of the loan. Equation (2.4) shows the time constraint with total time endowment given by T.

Similarly, the value function for the default case for singles is given by:

$$V^{D}_{S,g,j}(z_g) = \max_{n} u\left(c, l\right) + \beta \cdot \mathbb{E}_{z'_g,\kappa'}\left\{V_{S,g,j+1}(0, z'_g, \kappa')\right\} \tag{2.5}$$

s.t.

$$\begin{aligned} &c \leq (e_j \cdot z_g \cdot n) \cdot (1-\phi) \\ &l = T - n \end{aligned} \tag{2.6}$$

Note that in case of default, there is no asset choice to be made: In the period of default, no borrowing or saving is allowed ($a' = 0$). Equation (2.6) shows the budget constraint for the default case. All debts (or savings) a and expense shocks κ are discharged. In return, a fraction ϕ of the individual's wage is garnished.

Couples

Couples in my framework are modeled using a unitary approach. All choices are made jointly by the two individuals in a couple.[18]

Analogous to the case for singles, couples choose whether to jointly repay or default each period:

$$V_{C,j}(a, z_f, z_m, \kappa_f, \kappa_m) = \max\{V^{R}_{C,j}(a, z_f, z_m, \kappa_f, \kappa_m), V^{D}_{C,j}(z_f, z_m)\} \tag{2.7}$$

Here, the subscripts denote the female f or male m in a couple.

The repayment value function for couples is given by:

$$\begin{aligned} V^{R}_{C,j}(a, z_f, z_m, \kappa_f, \kappa_m) &= \max_{(a', n_f, n_m)} u\left(\frac{c}{\eta}, l_f\right) + u\left(\frac{c}{\eta}, l_m\right) \\ &+ \beta \cdot \Bigg((1-\psi) \cdot \mathbb{E}_{z'_f, z'_m, \kappa'_f, \kappa'_m}\left\{V_{C,j+1}(a', z'_f, z'_m, \kappa'_f, \kappa'_m)\right\} \\ &+ \psi \cdot \left(\mathbb{E}_{z'_f,\kappa'_f}\left\{V_{Div,f,j+1}(\frac{a}{2}, z'_f, \kappa'_f)\right\} + \mathbb{E}_{z'_m,\kappa'_m}\left\{V_{Div,m,j+1}(\frac{a}{2}, z'_m, \kappa'_m)\right\}\right)\Bigg) \end{aligned} \tag{2.8}$$

[18] A similar framework is used in Borella et al. (2021) for example.

s.t.

$$
\begin{aligned}
c + q_{C,j}^{(a')}(z_f, z_m) \cdot a' \leq e_j \cdot z_f \cdot n_f + e_j \cdot z_m \cdot n_m + a - \kappa_f - \kappa_m \\
l_f = T - n_f \\
l_m = T - n_m
\end{aligned}
\tag{2.9}
$$

In Equation (2.8) couples jointly maximize the sum of their individual utilities and their expected continuation value. Consumption in couples is adjusted by an equivalence scale η. This scale captures economies of scale in consumption within couples. With $\eta < 2$ couples can consume more than what they could consume if they were living separately. With probability ψ a couple gets hit by an exogenous divorce shock next period. Thus, with probability $(1 - \psi)$ the relevant continuation value is that of couples and with probability ψ it is the sum of the two divorced continuation values denoted by V_{Div}. I assume that in my model assets (or debts) get split 50-50 in the event of divorce.

Equation (2.9) shows the budget constraint. Note that couples are only allowed to save/borrow in one joint asset a'. Furthermore, each individual is subject to its own idiosyncratic productivity (z_f, z_m) and expense (κ_f, κ_m) shocks. Couples face their own loan pricing schedule q_C which is different from the one for singles q_S.

For the case of default, the value function is given by:

$$
\begin{aligned}
V_{C,j}^{D}(z_f, z_m) = \max_{(n_f, n_m)} u\left(\frac{c}{\eta}, l_f\right) + u\left(\frac{c}{\eta}, l_m\right) \\
+ \beta \cdot \Bigg((1 - \psi) \cdot \mathbb{E}_{z'_f, z'_m, \kappa'_f, \kappa'_m} \left\{ V_{C,j+1}(0, z'_f, z'_m, \kappa'_f, \kappa'_m) \right\} \\
+ \psi \cdot \left(\mathbb{E}_{z'_f, \kappa'_f} \left\{ V_{Div,f,j+1}(0, z'_f, \kappa'_f) \right\} + \mathbb{E}_{z'_m, \kappa'_m} \left\{ V_{Div,m,j+1}(0, z'_m, \kappa'_m) \right\} \right) \Bigg)
\end{aligned}
\tag{2.10}
$$

s.t.

$$
\begin{aligned}
c \leq (e_j \cdot z_f \cdot n_f + e_j \cdot z_m \cdot n_m) \cdot (1 - \phi) \\
l_f = T - n_f \\
l_m = T - n_m
\end{aligned}
\tag{2.11}
$$

The interpretation of Equation (2.10) is analogous to Equation (2.8). Note in

Equation (2.11) that in case of default a fraction ϕ of both spouses' income is garnished.

Divorced

The decision problem for divorced individuals is identical to the one for singles, except in the period of divorce in which an additional divorce cost has to be paid.

Divorced choose whether to repay or default each period:

$$V_{Div,g,j}(a, z_g, \kappa) = \max\{V^R_{Div,g,j}(a, z_g, \kappa), V^D_{Div,g,j}(z_g)\} \tag{2.12}$$

The repayment value function for divorced is given by:

$$V^R_{Div,g,j}(a, z_g, \kappa) = \max_{(a',n)} u\,(c, l) + \beta \cdot \mathbb{E}_{z'_g,\kappa'} \left\{ V_{S,g,j+1}(a', z'_g, \kappa') \right\} \tag{2.13}$$

s.t.

$$\begin{aligned} c + q^{(a')}_{S,g,j}(z_g) \cdot a' &\leq e_j \cdot z_g \cdot n + a - \kappa - \kappa_{Div} \\ l &= T - n \end{aligned} \tag{2.14}$$

Note that the continuation value in Equation (2.13) is the one for singles as the divorced problem is identical to the singles' one after the first period of divorce. For this reason the relevant pricing schedule in Equation (2.14) is also the one for singles. The divorce cost is captured by κ_{Div} and represents monetary costs from divorce such as lawyer fees.

The default value function for divorced is given by:

$$V^D_{Div,g,j}(z_g) = \max_{n} u\,(c, l) + \beta \cdot \mathbb{E}_{z'_g,\kappa'} \left\{ V_{S,g,j+1}(0, z'_g, \kappa') \right\} \tag{2.15}$$

s.t.

$$\begin{aligned} c &\leq (e_j \cdot z_g \cdot n) \cdot (1 - \phi) \\ l &= T - n \end{aligned} \tag{2.16}$$

Equation (2.16) shows that default also discharges the cost from divorce κ_{Div} in addition to other expense shocks.

2.4.2 Financial Intermediaries

Banks have access to funding at the exogenous, risk-free rate r_f. They operate in a perfectly competitive environment and every loan is priced such that it yields zero profit in expectation. Households differ in their default risk depending on their marital status, gender, age, and persistent wage. Furthermore, the loan size also plays a role for the default risk. Households are more likely to default on larger loans ceteris paribus. As a result, banks condition on all these variables when pricing their loans.

The bond price of a loan with size a' for a single S of gender g and age j with wage z is given by

$$q^{(a')}_{S,g,j}(z_g) = \\ = \begin{cases} \left(\mathbb{P}^{(a')}_{S,g,j}(z_g) \cdot 1 + (1 - \mathbb{P}^{(a')}_{S,g,j}(z_g)) \cdot \mathbb{E}\left(\frac{\Gamma}{a'+\kappa'}|d' = 1\right)\right) \cdot \frac{1}{1+r_f+\tau} & \text{if } a' < 0 \\ \frac{1}{1+r_f} & \text{if } a' \geq 0 \end{cases} \tag{2.17}$$

where τ is a borrowing wedge capturing the transaction cost of making loans. $\mathbb{P}$ denotes the repayment probability next period. If the household defaults, the bank will garnish a fraction ϕ of the wage. This leads to an expected recovery of $\mathbb{E}\left(\frac{\Gamma}{a'+\kappa'}|d' = 1\right)$, where $d' = 1$ indicates default.[19] The recovery Γ in case of default is given by

$$\Gamma = (e_{j+1} \cdot z'_g \cdot n') \cdot \phi$$

The loan bond price for a couple C of age j is given by

$$q^{(a')}_{C,j}(z_f, z_m) = \\ = \begin{cases} \left((1 - \psi) \cdot \mathbb{E}\{\hat{\mathbb{P}}_C\} + \psi \cdot (\frac{a}{2} \cdot \mathbb{E}\{\hat{\mathbb{P}}_{Div,f}\} + \frac{a}{2} \cdot \mathbb{E}\{\hat{\mathbb{P}}_{Div,m}\})\right) \cdot \frac{1}{1+r_f+\tau} & \text{if } a' < 0 \\ \frac{1}{1+r_f} & \text{if } a' \geq 0 \end{cases} \tag{2.18}$$

where $\mathbb{E}\{\hat{\mathbb{P}}_C\}$ and $\mathbb{E}\{\hat{\mathbb{P}}_{Div,g}\}$ denote expected repayment and recovery amounts from couples and divorced respectively. Recall that ψ denotes the probability of

[19]Note here that the garnished wage will be used to proportionally repay incurred expense shocks on top of the debt.

divorce. The expected repayment and recovery amounts are defined as below:

$$\mathbb{E}\{\hat{\mathbb{P}}_C\} = \overbrace{\mathbb{P}^{(a')}_{C,j}(z_f, z_m) \cdot 1}^{\text{repayment}} + \overbrace{(1 - \mathbb{P}^{(a')}_{C,j}(z_f, z_m)) \cdot \mathbb{E}\left(\frac{\Gamma_C}{a' + \kappa'_f + \kappa'_m}|d' = 1\right)}^{\text{recovery}}$$

$$\mathbb{E}\{\hat{\mathbb{P}}_{Div,g}\} = \mathbb{P}^{(a')}_{Div,g,j}(z_g) \cdot 1 + (1 - \mathbb{P}^{(a')}_{Div,g,j}(z_g)) \cdot \mathbb{E}\left(\frac{\Gamma_{Div,g}}{a' + \kappa' + \kappa_{Div}}|d' = 1\right)$$

where $\mathbb{P}$ again denotes the repayment probability next period. The recovery amounts in case of default are given by:

$$\Gamma_C = (e_{j+1} \cdot z'_f \cdot n'_f + e_{j+1} \cdot z'_m \cdot n'_m) \cdot \phi$$
$$\Gamma_{Div,g} = (e_{j+1} \cdot z'_g \cdot n'_g) \cdot \phi$$

2.4.3 Equilibrium

Given a risk-free rate r_s a recursive competitive equilibrium is given by a set of value functions (V^R_S,V^D_S,V^R_C,V^D_C,V^R_{Div},V^D_{Div}), a set of policy functions (c_S,c_C,c_{Div},a'_S, a'_C,a'_{Div},d'_S,d'_C,d'_{Div},n_S,$n_{C,f}$,$n_{C,m}$,n_{Div}), and a set of bond pricing functions (q_S,q_C) such that:

1. The value functions satisfy Equations (2.1), (2.2), (2.5), (2.7), (2.8), (2.10), (2.12), (2.13), (2.15).

2. The policy functions are the associated optimal policy rules.

3. The bond price schedules satisfy the zero profit conditions (2.17) and (2.18).

I compute the equilibrium value functions, policy functions, and bond price schedules by backward induction starting at the final age period. Further computational details are given in Appendix 2.A.

2.5 Calibration

I choose the baseline calibration year as 2019 and calibrate the model to the U.S. population. There are three sets of parameters: (1) Those that are standard and which I take from the literature, (2) parameters that I exogenously calibrate to direct empirical counterparts, and (3) parameters that I internally calibrate to have the model match certain data moments. Table 2.1 contains an overview of all exogenously chosen parameters, whereas Table 2.2 lists the internally calibrated parameters. Table 2.3 summarizes the targeted moments used for the calibration.

I assume that individuals may choose to work full-time ($n = 1$), part-time ($n = 0.5$) or not at all ($n = 0$). The utility function is given by

$$u(c_t, l_t) = \frac{(c_t^{\omega} l_t^{1-\omega})^{1-\gamma}}{1-\gamma}$$

where γ is the risk aversion coefficient and which I set to 2 which is a standard value in the macro literature. ω denotes the utility weight of consumption and is important for the labor supply choice of individuals. I thus internally calibrate this parameters to match the average hours worked of singles at age 50 as estimated by Borella, De Nardi, and Yang (2018). This yields a value of $\omega = 0.56$. The annual discount factor is calibrated to match the fraction of households in the Survey of Consumer Finances (SCF) 2019 with negative net worth.[20] I restrict the SCF sample to households with a head aged between 20 and 68 in line with my model. This results in an annual value of about 0.973 (and thus $\beta = 0.973^3 = 0.92$).

The persistent wage process is taken from Borella et al. (2018). I use their estimated wage process because they estimate wage processes separately for men and women using PSID data. The authors assume an AR(1) process in log wages: $\ln z^i_{g,t+1} = \rho_g \ln z^i_{g,t} + \epsilon^i_{g,t}, \epsilon^i_{g,t} \sim N(0, \sigma^2_{\epsilon,g})$ for gender $g \in \{f, m\}$. The estimated process for women shows slightly lower persistence than the one for men ($\rho_f = 0.963$ vs. $\rho_m = 0.973$) and a smaller shock variance ($\sigma^2_{\epsilon,f} = 0.014$ vs. $\sigma^2_{\epsilon,m} = 0.016$). I convert their annual estimates to triennial values and then discretize them into two five-state Markov processes using the Rouwenhorst method. The lifecycle productivity profile is taken from Gourinchas and Parker (2002).[21]

I set the risk-free savings rate to 3.44% following Gourinchas and Parker (2002).[22] This implies a three-year risk-free rate on savings of 10.68%. The

[20]The definition of net worth follows Herkenhoff (2019). It is computed as the difference between a household's liquid assets, such as checking and savings accounts, and credit card debt. I prefer this measure of net worth as my model does not include illiquid assets like housing.

[21]This profile is also used in Livshits et al. (2007) and Livshits et al. (2010).

[22]This is the value used in Livshits et al. (2010). Voena (2015) uses a similar value of 3%.

Parameter	Symbol	Value	Source
Income processes			
Persistence, women	ρ_f	0.963	Borella et al. (2018)
Persistence, men	ρ_m	0.973	Borella et al. (2018)
Variance, women	$\sigma^2_{\epsilon,f}$	0.014	Borella et al. (2018)
Variance, men	$\sigma^2_{\epsilon,m}$	0.016	Borella et al. (2018)
Lifecycle productivity	e_j		Livshits et al. (2010)
Expense shocks	κ		Own (MEPS data)
Annual savings rate	r_f	3.44%	G-P (2002)‡
Total weekly time endowment	T	60 hours	Alon et al. (2020)
Risk aversion coefficient	γ	2	Standard
Annual probability for divorce	$\frac{\psi}{3}$	1.1%	ACS* (2019)
Divorce cost	κ_{Div}	\$11,300	M-N Research† (2019)
Equivalence scale in couples	η	1.64	Voena (2015)

Table 2.1: Exogenously Chosen Parameters

Notes: ‡ Gourinchas and Parker (2002), * American Community Survey, † Martindale-Nolo Research (2019).

transaction cost of lending τ is calibrated internally to match the average interest rate on credit cards in the 2019 SCF. I again restrict the sample to household heads aged between 20 and 68 and also exclude households that report no credit card debt or a non-positive interest rate.[23] This results in an annual value for the transaction cost of lending of 0.93%. Together with the risk-free savings rate, this implies a three year risk-free lending rate of around 13.7%.[24] The wage garnishment rate is crucial for the amount of default in the economy. I set it to $\phi = 0.395$ to match the number of Ch. 7 bankruptcies per household in the U.S. in 2019 as reported by the American Bankruptcy Institute. Total time endowment $T = 1.5$ is taken from Alon, Doepke, Olmstead-Rumsey, and Tertilt (2020). For a full-time job of $n = 1$ corresponding to 40 hours, this value for T implies a total weekly time endowment of 60 hours.

The parameters governing the divorce shock are calibrated as follows: The probability of a divorce shock is pinned down by the divorce rate in the U.S. using data from the 2019 American Community Survey. This yields an annual

[23] I exclude observations with no credit card debt as these households use credit cards for transactional, and not borrowing, purposes. I leave out observations with non-positive interest rates as these are usually temporary promotional rates.

[24] $(1 + 0.0344 + 0.0093)^3 \approx 1.1369$

Parameter	**Value**	**Data Target**
Annual Discount factor	0.97	Frac. of HH with neg. net worth
Consumption weight	0.56	Avg. hours of singles at 50
Wage garnishment rate	0.395	Ch. 7 bankruptcies per HH
Ann. transaction cost of lending	0.93%	Avg. credit card interest rate

Table 2.2: Internally Calibrated Parameters

Notes: Source for fraction of HH with neg. net worth: Survey of Consumer Finances 2019. Source for avg. hours of singles at 50: Borella et al. (2018). Source for Ch. 7 bankruptcies per HH: American Bankruptcy Institute. Source for avg. credit card interest rate: Survey of Consumer Finances 2019.

Moment (in %)	**Data**	**Model**
Default rate (aggregate)	1.1	1.1
Fraction of borrowers (aggregate)	20.7	20.7
Avg. interest rate (aggregate)	16.3	16.3
Avg. hours of singles at 50	1786	1795

Table 2.3: Targeted Moments

divorce rate of 1.1% resulting in a three-year rate of 3.3%. The costs of divorce are taken from a survey conducted by Martindale and Nolo Research in 2019.[25] Their survey gives an estimate of average legal costs of divorce in 2019 of $11,300.

The equivalence scale for consumption in couples is taken from Voena (2015). She calibrates the degree of economies of scale for couples to 1.4023, which implies an equivalence scale of 1.64.[26]

As it turns out, expense shocks are crucial for welfare implications. Thus, I estimate these shocks myself in order to allow for heterogeneity in expenses across marital status and age. The next subsection details my procedure.

[25] See also `https://www.nolo.com/legal-encyclopedia/ctp/cost-of-divorce.html`.

[26] More specifically, she models spousal consumption as $x = ((c^H)^\rho + (c^W)^\rho)^{\frac{1}{\rho}}$, where x are household expenditures and c^H (c^W) is the consumption of the husband (wife). Assuming that consumption is split equally between husband and wife (as is the case in my model), $\rho = 1.4023$ implies an equivalence scale of 1.64.

2.5.1 Expense Shocks

The previous literature has highlighted several sources of unexpected expenses which are important to consider for the bankruptcy decision of households. Among these sources are out-of-pocket medical, divorce, and childcare expenses resulting from unplanned pregnancies, see e.g. Livshits et al. (2007). As my framework explicitly models divorce, I include divorce expenses in the divorce shock instead of the expense shock. Furthermore, my model abstracts from children and childcare. As such, I also abstract from childcare expenses when estimating the expense shock to feed into my model.

To estimate medical expenses I use data from the Medical Expenditure Panel Survey (MEPS) from the years 2018 and 2019. The MEPS features an overlapping cohorts design and follows each cohort for two years. It collects detailed information on medical expenditures of households and includes many demographic attributes. In particular, MEPS also collects the source of payment. This is important because medical expenses relevant for the bankruptcy decision of households are those that have to be paid by themselves (out-of-pocket).[27]

To estimate these shocks I largely follow the approach laid out in Livshits, MacGee, and Tertilt (2003). I focus on Panel 23 which covers the years 2018 and 2019. There are two issues with using out-of-pocket spending reported in MEPS out of the box for my estimation.

The first issue is that MEPS underreports out-of-pocket medical spending compared to aggregate sources. Average per capita out-of-pocket spending in MEPS for 2018 (2019) in Panel 23 was \$826.45 (\$834.01). Using National Health Expenditure Data the same figure for 2018 (2019) was \$1184.39 (\$1233.06).[28] Under the assumption that the factor of underreporting is constant across the population, I adjust MEPS out-of-pocket expense numbers in 2018 (2019) by a factor of 1.43 (1.48).

The second issue is that out-of-pocket medical spending in MEPS does not include bad debts, i.e. medical bills unpaid by households. However, these bills are part of the medical expenses faced by households and influence households' default behavior. As such I construct a measure of medical expenses by adding bad debt to the out-of-pocket spending reported in MEPS. The American Hos-

[27] As opposed to payments covered by insurance.

[28] Total out-of-pocket medical expenditures in 2018 (2019) were \$386.5 billion (\$403.7B billion). The total U.S. civilian non-institutionalized population in 2018 (2019) was 326 million (327 million).

pital Assocation (2020) reports total U.S. uncompensated hospital care cost in 2018 (2019) of \$41.3 billion (\$41.61 billion).[29] This corresponds to 3.68% (3.49%) of total U.S. hospital spending in 2018 (2019).[30] Assuming that this ratio also holds for the total medical sector, I get an estimate of bad debt in the U.S. medical sector of \$111.2 billion (\$110.81 billion) for 2018 (2019).[31] I allocate this sum to all individuals in the MEPS data who were not insured in at least one month of 2018 (2019) proportional to the difference between their charges and expenditures.

More specifically, I compute adjusted out-of-pocket medical expenses $\widetilde{OOP}_i^Y$ facing an individual i in year Y in the following way:

$$\widetilde{OOP}_i^Y = a^Y \cdot OOP_i^Y + b^Y \cdot I_i^Y \cdot (charge_i^Y - exp_i^Y) \tag{2.19}$$

where $a^{2018} = 1.43$ ($a^{2019} = 1.48$) is the adjustment factor from before. OOP are the out-of-pocket expenses recorded in MEPS, b^Y is a factor to allocate the previously estimated aggregate bad debt to individuals, and I is an indicator whether an individual was uninsured for at least one month. $charge_i^Y$ are the total medical charges facing an individual i and exp_i^Y are the total medical expenses paid by any source. The difference (interacted with the insurance status) is thus a measure of individual bad debt.

A period in my model lasts three years. As such, I want to estimate medical expenses over a three year period. However, MEPS only follows each panel for two years. To construct medical expenses in the third year while taking into account potential persistence in these expenses I first estimate the following regression:

$$\widetilde{OOP}_i^{Y2} = \alpha + \beta \cdot \widetilde{OOP}_i^{Y1} + \epsilon_i \tag{2.20}$$

I find estimated values of $\hat{\alpha} = 654.56$ and $\hat{\beta} = 0.47$.

Then, I estimate the third year expenses using these estimated parameters:

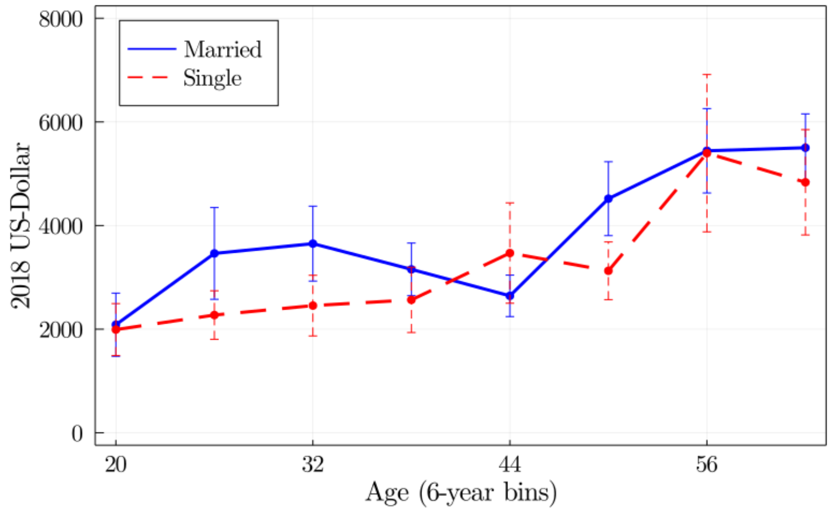
$$\widehat{\widetilde{OOP}}_i^{Y3} = \hat{\alpha} + \hat{\beta} \cdot \widetilde{OOP}_i^{Y2} + e_i$$

[29] Uncompensated care is a measure of care for which the hospital received no payment from patient or insurer. It includes bad debts and financial assistance provided by the hospital.

[30] National Health Expenditure Data reports total U.S. hospital spending in 2018 (2019) of \$1122.6 billion (\$1193.7 billion).

[31] National Health Expenditure Data reports total personal health care expenditures in 2018 (2019) of \$3021.8 billion (\$3175.2 billion).

Figure 2.1: Average Per Capita 3-Year Out-of-Pocket Medical Expenses



Notes: Confidence bands are 2 SE. Out-of-pocket medical expenses are costs that are not covered by insurance and have to be paid by the patients themselves.

where e_i is drawn from the residual distribution of (2.20). The final 3-year expense is the sum of the expenses in year one, two, and three.

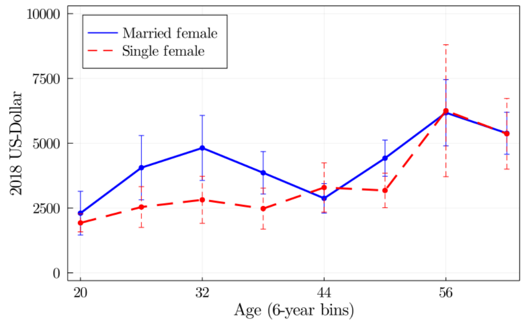
Figure 2.1 plots the estimated average per capita 3-year out-of-pocket medical expenses across six-year age bins. We can see that these expenses amount to thousands of US-Dollars. Unsurprisingly, medical expenses also tend to increase as people get older. Married individuals seem to have slightly higher mean expenses in their late 20s and early 30s compared to singles. Figure 2.2 offers a more disaggregated view. In the top row, we can see that the higher medical expenses for married individuals are primarily driven by married females. One plausible explanation is that these reflect higher expenses due to pregnancy and childbirth.[32]

In my model, expense shocks depend on marital status as well as age and can have three realizations: $\kappa^{age}_{status} = \{0, \kappa 1^{age}_{status}, \kappa 2^{age}_{status}\}$. To translate the estimated medical expenses into my model, I first subset the data across marital status and age. I categorize individuals into married, single (including divorced), and others, as well as six-year age groups. Note that I subset the sample into six-year age bins due to sample size limitations. As a model period lasts three years, two consecutive age groups in the model face the same expense

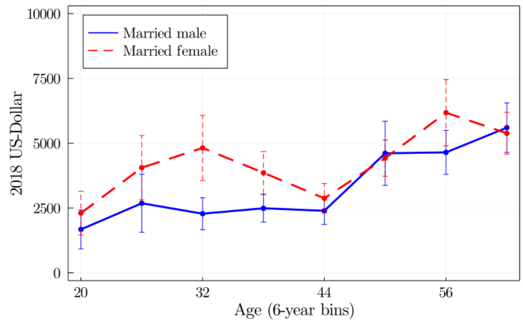
[32]For additional results showing the distribution of expenses across singles and couples, see Appendix 2.C.

Figure 2.2: Avg. Per Capita 3-Year OOP Medical Expenses - Detailed View

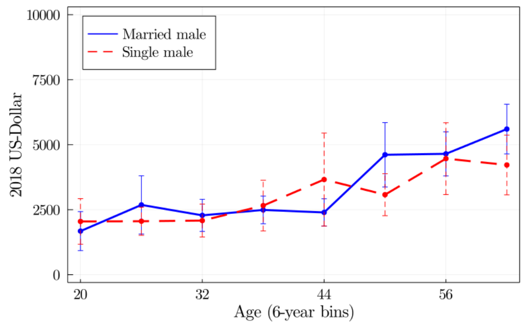
(a) Married Female and Single Female



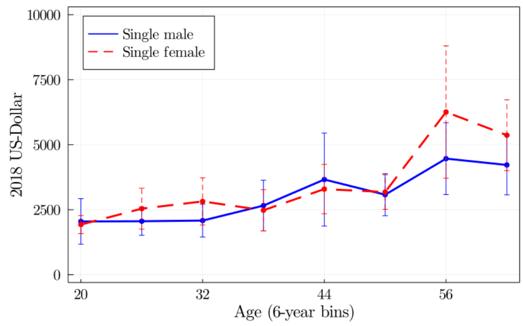
(b) Married Male and Married Female



(c) Married Male and Single Male



(d) Single Male and Single Female



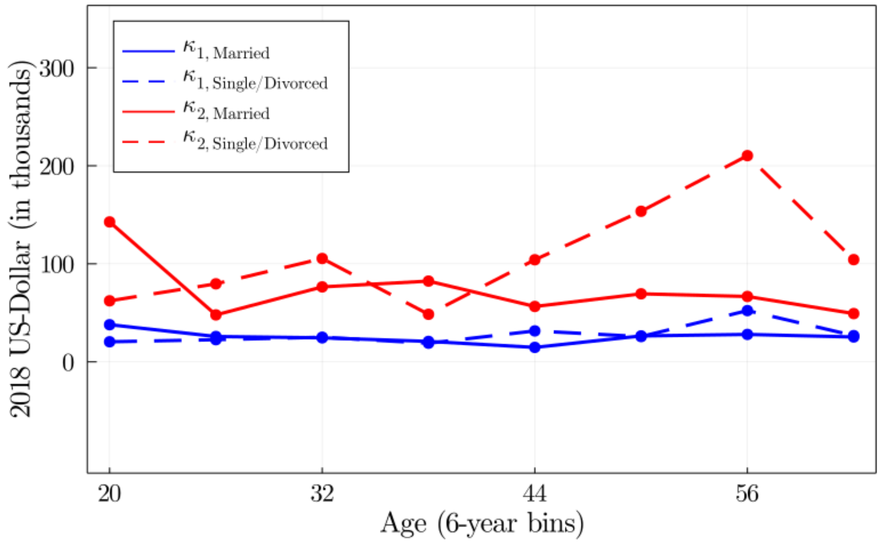
Notes: Confidence bands are 2 SE. Out-of-pocket medical expenses are costs that are not covered by insurance and have to be paid by the patients themselves.

shocks.[33] In order to compute the kind of medical expenses that can trigger default, I focus on the largest estimated expenses and compute the 95th and 98th percentile for each subset. The large shock κ_2 is pinned down by the mean expense of the top 2%. The smaller shock κ_3 is determined by the mean expense of the next 3%. The corresponding shock probabilities in my model are thus: $\pi_\kappa = \{0.95, 0.03, 0.02\}$. Figure 2.3 illustrates the estimated magnitudes of the expense shock process $\kappa_{status}^{age} = \{0, \kappa_{1status}^{age}, \kappa_{2status}^{age}\}$. One can see that these large medical expenses can amount to several hundred thousand US-Dollars. In addition, single and divorced individuals have larger expenses compared to married at later ages.[34]

[33]For example, 20-22 and 23-25 year old individuals face the same expense shocks in the model.

[34]For additional results regarding the estimation of expenses, see Appendix 2.B.

Figure 2.3: Estimated Expense Shock Magnitudes



Notes: Source: MEPS (2019). κ_1 is computed as the mean out-of-pocket expenses among the 95th to 98th percentile. κ_2 is computed as the mean out-of-pocket expenses among the 98th to 100th percentile.

2.5.2 Model Validation

I evaluate my model fit on a set of untargeted moments that are commonly used in the literature. The results are summarized in Table 2.4.

Note that while I target the aggregate default rate, fraction of borrowers, and average interest rate in my calibration, the moments for the various subgroups (singles, couples, and divorced) were not used. Regarding default rates, I use data from the American Bankruptcy Institute for the aggregate default rate. However, the institute does not publish default rates across marital status. Instead, I use the Survey of Consumer Finances 2019 to compute default rates across marital status. One can see that my model manages to generate default rates that are higher for singles and in particular divorced households relative to couples as in the data. For the fraction of borrowers, my model overpredicts borrowing by singles compared to the data but replicates the higher need for borrowing among divorced relative to couples. Similarly, my model generates a too high interest rate for singles but reflects how divorced households face more expensive loans than couples.

The debt-to-income (DTI) ratio conditional on borrowing in the data is computed using the SCF 2019. For my measure of debt, I use the same net

Moment (in %)	Data	Model
Default rate*		
Default rate, Singles	0.85	1.56
Default rate, Couples	0.84	0.67
Default rate, Divorced	1.36	1.89
Fraction of borrowers		
Fraction of borrowers, Singles	20.2	24.2
Fraction of borrowers, Couples	20.4	18.5
Fraction of borrowers, Divorced	23.3	21.7
Avg. interest rate		
Avg. interest rate, Singles	16.2	17
Avg. interest rate, Couples	16.1	15.7
Avg. interest rate, Divorced	16.8	16.7
Debt-to-Income Ratio (cond. on borrowing)	15.2	25.7
DTI, Singles	14.8	34.5
DTI, Couples	13.6	20.3
DTI, Divorced	20.9	26.8

Table 2.4: Untargeted Moments

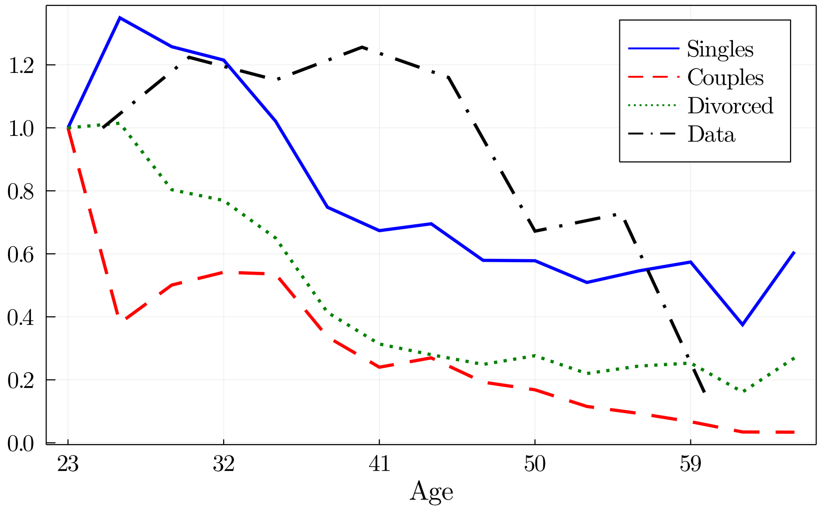
Notes: * The American Bankruptcy Institute does not publish default rates across marital status. Instead, the default rates for the subgroups are computed using the Survey of Consumer Finances 2019.

worth definition following Herkenhoff (2019) described earlier. First, I compute for each household with negative net worth the ratio of net worth and wage income.[35] Then, I winsorize the top 1% of the resulting distribution following Herkenhoff (2019) as I consider these observations as outliers with outsized influence on the mean. Finally, I compute the average ratio for all households with heads aged between 20 and 68. The DTI ratio in the model is similarly derived by computing the ratio of debt to income for all households with negative assets and then averaging. Overall, my model overpredicts indebtedness for all subgroups.

Figure 2.4 depicts bankruptcy filing rates across age for singles, couples, and divorced in my model (normalized so that every series starts at one). The

[35]I focus on wage income as my measure of income in the data as this is most in line with my model setup.

Figure 2.4: Bankruptcy Filing Rates (Normalized) Across Age



Notes: The series are normalized such that each series starts at one. "Singles", "Couples", and "Divorced" denote the bankruptcy filing rates for the respective household groups in my model after normalization. The data series is taken from Sullivan et al. (2000).

data numbers are taken from Sullivan et al. (2000).[36] Note that my model is calibrated to the year 2019, whereas the data come from a much earlier time period (pre 2000). My model matches the overall decline in bankruptcy rates over the lifetime but overpredicts filings rates for younger households. This is driven by the fact that in the model young households borrow heavily to smooth consumption over their lifetime. This causes an increase in defaults in turn.

2.6 Welfare Analysis

In this section I analyze the welfare implications of my model. In particular, I am interested in whether single households and couples differ in their preferred leniency of the bankruptcy regime.

In theory, the welfare-maximizing bankruptcy leniency is unclear ex-ante. There are two opposing forces at work: On the one hand, a more lenient bankruptcy regime (corresponding to a lower garnishment rate in my model) makes bankruptcy less costly for households. Thus, households can default more

[36] Unfortunately, it is not possible to plot bankruptcy filing rates across age and marital status using the Survey of Consumer Finances. Bankruptcy is too rare as an event and the sample size of the survey is not large enough.

cheaply when hit by a bad shock in order to smooth their consumption. In the literature, this channel is commonly referred to as smoothing consumption *over states*. On the other hand, a more lenient bankruptcy regime makes it more likely for households to default c.p. Financial intermediaries anticipate this and will require a higher default premium. As a result, lower default costs lead to higher interest rates on loans and make smoothing consumption *over time* more difficult.[37]

To measure welfare across different garnishment rates I use the ex-ante well-being of single women and men as well as of couple households. That is, I use the following welfare criterion:

$$
\begin{aligned}
W_S &= \mathbb{E}_{z_g}\left\{V_{S,g,j=0}(a=0, z_g, \kappa=0)\right\} \\
W_C &= \mathbb{E}_{z_f,z_m}\left\{V_{C,j=0}(a=0, z_f, z_m, \kappa_f=0, \kappa_m=0)\right\}
\end{aligned}
\tag{2.21}
$$

Recall that all newborns ($j=0$) start life with no assets ($a=0$) and no expense shock ($\kappa=0$), but that there is heterogeneity regarding the starting wage (z_g).[38]

2.6.1 Baseline

In this section I examine the welfare implications of varying the leniency of the bankruptcy regime by changing the garnishment rate ϕ between 0.1 and 0.9. Figure 2.5 illustrates the resulting welfare curves for single female and male as well as couple households. We can see that there are sharp differences regarding the preferred bankruptcy leniency between single and couple households. Whereas single households prefer intermediate garnishment rates in the range between 0.3 and 0.5, couples prefer a more lenient regime with a garnishment rate of 0.1.[39]

2.6.2 Decomposition

What are the channels that drive the heterogeneous welfare implications for single versus couple households in the previous section? Single and couple

---

[37] See also Zame (1993).

[38] As I am only interested in the shape of the welfare curve (the location of the maximum in particular), there is no need to convert this welfare measure into consumption equivalent variation.

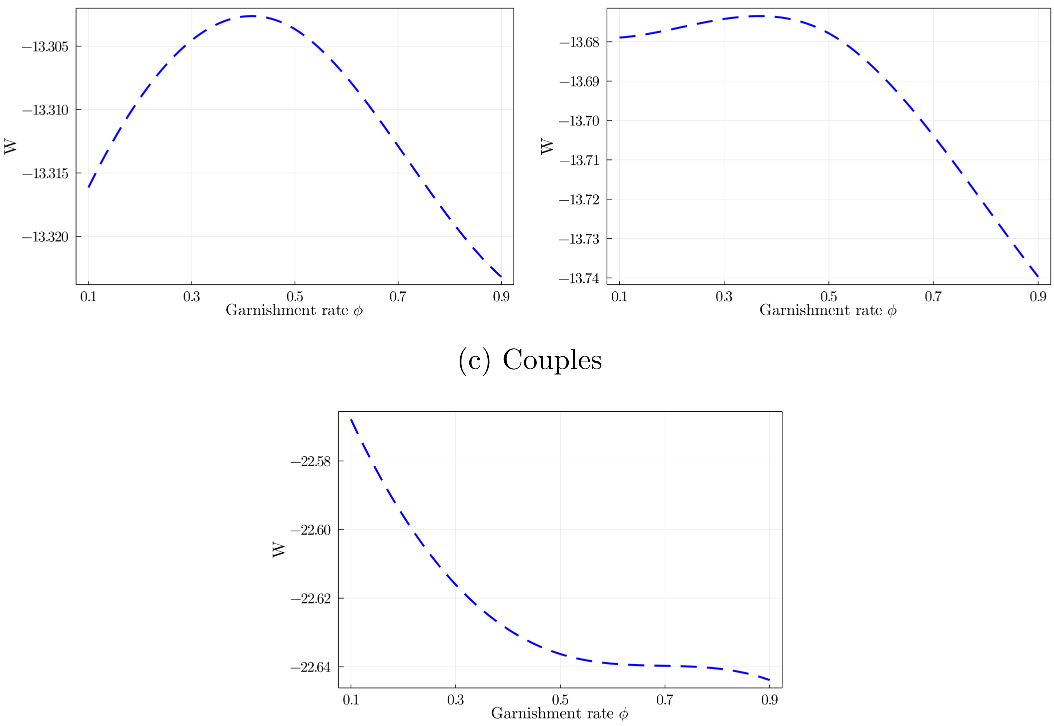
[39] The differences between single women and men are driven by heterogeneity between their wage processes.

Figure 2.5: Welfare - Baseline

(a) Single Women

(b) Single Men

(c) Couples



Notes: The welfare measure W is defined in Equation (2.21).

households differ in a number of ways:

1. **Income side**: In couple households, each individual is subject to their own wage process. In addition, each spouse can choose his/her labor supply. Single households by nature are only subject to one wage process.

2. **Expense side**: Both spouses in couple households are subject to their own expense shock process. This implies that couple households are hit by at least one expense shock more often than single households.

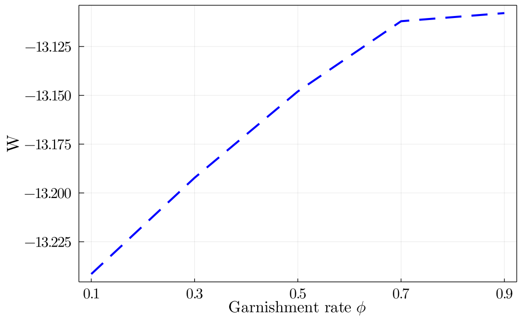
3. **Divorce channel**: Couple households are subject to a divorce shock, singles are not. The divorce itself is costly.

4. **Economies of scale**: Couples households enjoy economies of scale in consumption, singles do not.

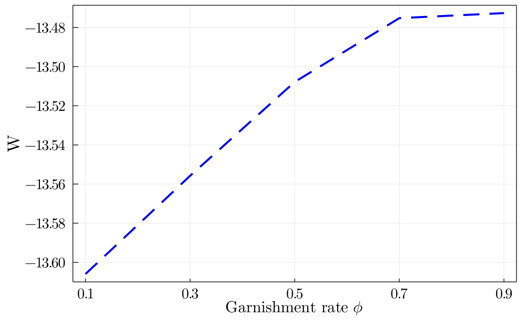
In the following of this section, I separately look at each of these channels

Figure 2.6: Welfare - Only Income Differences between Singles and Couples

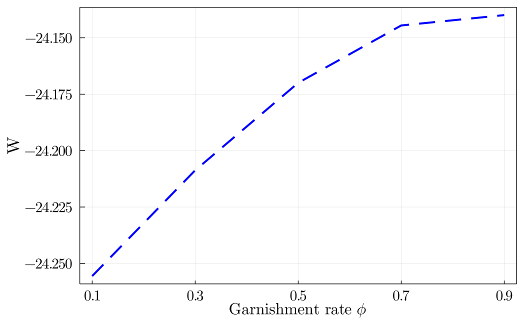
(a) Single Women



(b) Single Men



(c) Couples



Notes: The welfare measure W is defined in Equation (2.21). In this experiment, all expense shocks, divorce shocks, and economies of scale in consumption are turned off. The only remaining differences between singles and couples are on the income side.

in turn and examine to what extent they drive the baseline welfare results in Section 2.6.1.

Income Side

To start off, I first look at the effects of differences on the income side between singles and couples. Recall from Section 2.4.1 that I model wage processes at an individual level. Thus, singles are subject to one wage process while each individual in a couple is subject to its own wage process.

In order to isolate the income side, I turn off the divorce shock and economies of scale for couples as well as all expense shocks. Figure 2.6 shows the resulting welfare curves across different garnishment rates for singles and couples. We can see that in this counterfactual all households prefer a very strict bankruptcy regime with a garnishment rate of 0.9. This result is primarily driven by the removal of expense shocks. Without expense shocks households no longer have any need for bankruptcy to discharge large expenses. As a result, the benefit of a lenient bankruptcy regime is reduced as smoothing over states becomes less important.

There is a large literature that examines risk-sharing within families.[40] One result from this literature is the existence of the so-called *intra-household insurance channel*. Within a family, spousal labor supply acts as an additional insurance mechanism against labor shocks. A spouse can adjust his or her labor supply in response to the partner's wage realization.

This channel is also active in my model. One way to illustrate it is by examining the degree of consumption insurance available to singles versus couples. To do so, I use my calibrated model with the benchmark garnishment rate, where all expense shocks, divorce shocks, and economies of scale remain turned off, to simulate a household panel of marital status, consumption and labor productivity. I then use the simulated data to run the following regression separately for single or married individuals i:[41]

$$\Delta \log(c_{it}) = \delta + \mu \cdot \Delta \log(z_{it}) + \nu_1 \cdot age_{it} + \nu_2 \cdot age_{it}^2 + \epsilon_{it}$$

where I regress log changes in productivity z_{it} on log changes in consumption c_{it} while controlling for age and the square of age. The coefficient of interest is μ which measures the degree to which changes in labor productivity pass-through to changes in consumption. A higher value for μ indicates a higher pass-through and thus a lower degree of consumption insurance. I find that in my model couples enjoy a stronger degree of consumption insurance: The estimated coefficient for singles is $\hat{\mu}_S = 0.88$ whereas the one for couples is $\hat{\mu}_C = 0.43$.

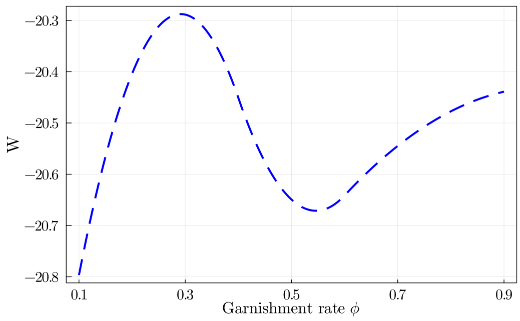
Intuitively, the existence of an additional mechanism to smooth consumption over states for couples should mean that they rely less on default to smooth over states relative to singles. As a result, couples should prefer a stricter bankruptcy regime compared to singles. Figure 2.7 shows that this is indeed the case. In order to understand the effect of the intra-household insurance channel on the preferred bankruptcy regime it is necessary to get an interior

[40] See Section 2.2 for an overview.

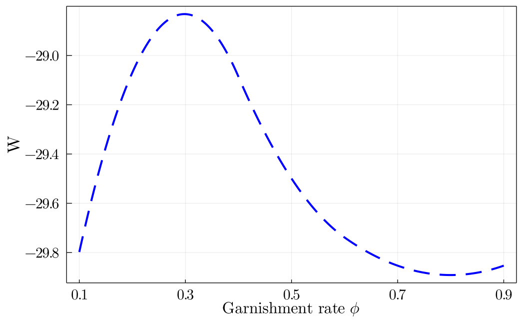
[41] This regression has been used in the literature to measure the degree of consumption insurance in data by for example Blundell et al. (2008) and in simulated data by Voena (2015) among others.

Figure 2.7: Welfare - Effect of Intra-Household Insurance Channel

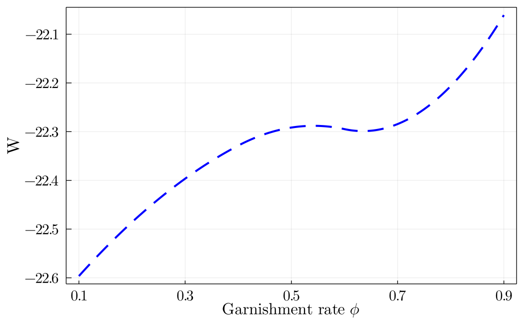
(a) Single Women



(b) Single Men



(c) Couples



Notes: The welfare measure W is defined in Equation (2.21). In this experiment, all expense shocks, divorce shocks, and economies of scale in consumption are turned off. The only remaining differences between singles and couples are on the income side. In addition, the standard deviations of the income processes are artificially inflated by a factor of fifteen in order to generate an interior optimum for at least one group.

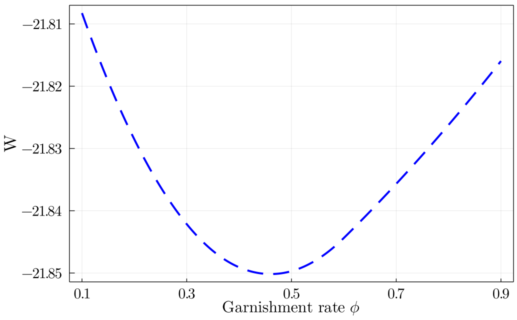
optimum for one of the household types (either singles or couples). To do so, I artificially multiply the standard deviations of the income processes by fifteen times in Figure 2.7 compared to Figure 2.6.[42] We can see that now couples prefer a higher garnishment rate compared to singles, in line with the intuition.

The conclusion from these experiments is that the income side cannot explain why couples prefer a more lenient bankruptcy regime than singles in the baseline. In fact, as Figure 2.7 shows, differences on the income side should make couples prefer a **stricter** regime relative to singles. As a result, there must be a counteracting force among one (or several) of the remaining channels.

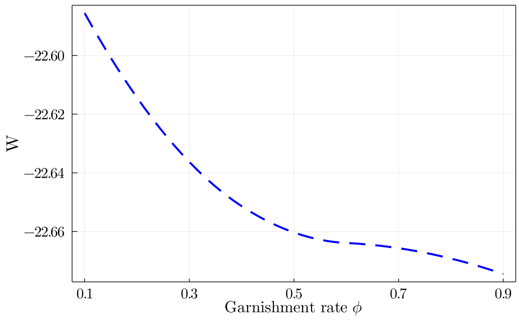
[42]The exact multiplier is chosen arbitrarily. It only needs to be large enough to generate an interior optimum.

Figure 2.8: Welfare of Couples - Experiments

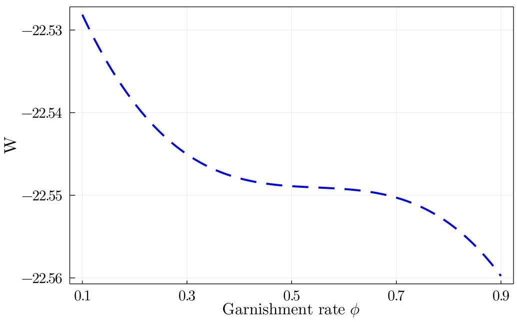
(a) No Divorce



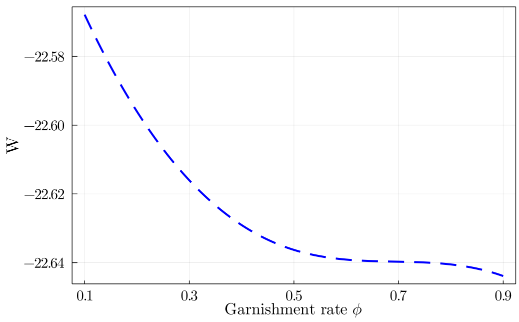
(b) Couples have Single Expenses



(c) Couples have Only One Single Expense



(d) Baseline



Notes: The welfare measure W is defined in Equation (2.21). "No divorce" describes the experiment where the divorce shock for couples is turned off. "Couples have single expenses" refers to the experiment where the calibrated expense process for married individuals is replaced by the one for singles. "Couples have only one single expense" refers to the experiment where additionally, couples are subject to only one expense process instead of two.

Expense Side and Divorce

In this section I investigate to what extent the expense side and the divorce shock can explain the welfare findings from Section 2.6.1. To do so, I start with the baseline model and eliminate the differences between singles and couples for each channel one at a time. The results are depicted in Figure 2.8.

To examine the influence of the divorce channel, I turn off the divorce shock for couples by setting the probability of the shock to 0. Figure 2.8a shows that even after turning off the divorce shock couples still prefer the most lenient bankruptcy regime. Figure 2.8d depicts the baseline welfare results of couples for comparison. We can see that compared to the baseline case higher garnishment rates become relatively more appealing as the welfare curve displays a U-shape. Thus, while the divorce channel alone cannot explain why couple households prefer a lower garnishment rate than singles, it seems to be one important driver.

The expense side is somewhat more complicated. First, singles differ from couples in terms of their calibrated expense shock process. In particular, the expense shock sizes of a single individual differ from those of a married individual.[43] Moreover, I model expense shocks at the individual level. Single households are thus subject to one expense shock process whereas couples are subject to two. In order to disentangle these two channels, I first replace the expense shock process for married individuals using the one for singles. I call this experiment "Couples have single expenses." Figure 2.8b shows that the welfare curve in this case looks similar to the baseline case. I thus conclude that differences in the calibration of the expense shock processes are not the main driver behind the welfare findings.

Next, I assume that in addition couples are only subject to one expense shock process instead of two. This means that the expense side of singles is now identical to the one of couples. I name this experiment "Couples have only one single expense." Figure 2.8c illustrates that couples still prefer the most lenient bankruptcy regime. However, compared to the baseline the welfare curve now is much flatter (notice the different y-axis scaling).[44]

Economies of Scale

One final difference between singles and couples is that couples benefit from economies of scale in consumption. Again starting from the baseline model, I turn off economies of scale in couples' consumption by setting $\eta = 2$. Figure 2.9 illustrates that this barely affects the shape of the welfare curve across garnishment rates compared to the baseline in Figure 2.8d. As a result, I conclude that economies of scale are not the feature that drive the baseline welfare results.

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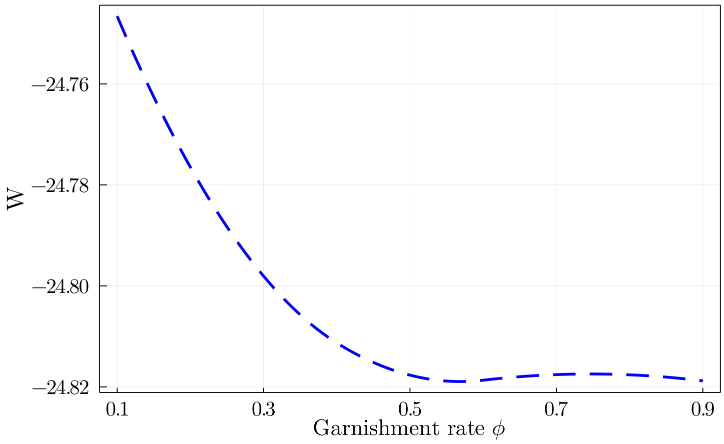
[43] See also Section 2.5.1.

[44] In Appendix 2.C I show the welfare result when I assume that the expense shock processes within couples are perfectly correlated.

Figure 2.9: Welfare of Couples - No Economies of Scale



Notes: The welfare measure W is defined in Equation (2.21). "No economies of scale" refers to the experiment where couples do not benefit from economies of scale in consumption.

Combinations of Different Channels

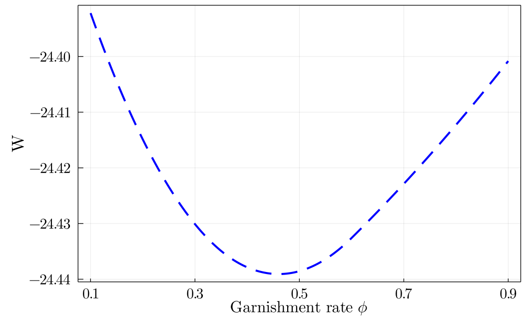
Putting these results together, we can see that no channel by itself can explain the finding that couples prefer the most lenient bankruptcy regime. Thus, it must be a combination of channels. Figure 2.10 depicts different combinations of the previous experiments. For example, in Figure 2.10a I turn off both the the divorce shock as well as the economies of scale in consumption for couples. We can see in Figure 2.10c that turning off the divorce shock and making the expense side of couples identical to the one for singles is key to explaining why couples prefer the most lenient regime in the baseline.

Table 2.5 summarizes the previous experiments. The baseline welfare result, that couples prefer more lenient bankruptcy, is driven by two factors: 1) Default is an important insurance mechanism against divorce for couples. This channel does not exist for singles. 2) A more lenient bankruptcy makes it cheaper to default in response to expense shocks. Couples benefit in particular from this channel because they are hit by expense shocks more often.

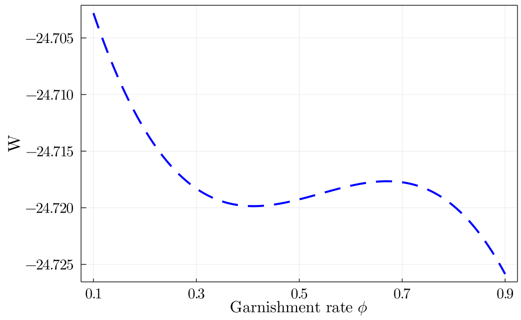
Regarding the first point, it is unsurprising to see that divorce is a factor that makes couples prefer a more lenient bankruptcy regime. First, a divorce shock itself is costly and can be seen as a type of expense shock. Second, a divorce transforms one couple into two single households. Singles do not have access to intra-household insurance increasing their risk from wage fluctuations. Figure 2.11 shows how default behavior among households evolves around divorce. We

Figure 2.10: Welfare of Couples - Experiments - Combinations

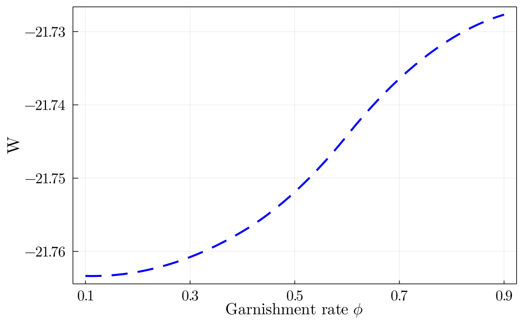
(a) No Divorce and No Economies of Scale



(b) No Scale, Only One Single Expense



(c) No Divorce, Only One Single Expense



Notes: The welfare measure W is defined in Equation (2.21). "Only one single expense" refers to the experiment where the expense side of couples is identical to the one of singles.

can see that the default rate quadruples at the time of divorce (event time equal to 0). Naturally, a higher garnishment rate makes default after divorce more costly.

For the second point, I compute the fraction of households that default conditional on receiving any expense shock in the baseline. Figure 2.12 summarizes the results. In the left figure I depict the fraction of singles that default after receiving any expense shock (blue, solid line), a small expense shock (red, dashed line) or a large shock (green, dash-dotted line). The right figure shows the fraction of couples that default after receiving any expense shock (blue, solid line), one small shock (red, solid), two small shocks (red, dashed), one large shock (green, solid), one large and one small shock (black, dash-dotted), or two large shocks (green, dashed).

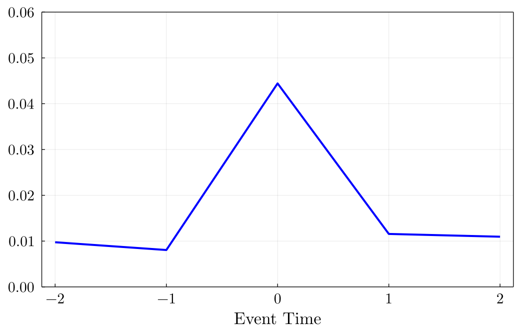
For couples the fraction of households that default after receiving one small

Experiment	**Couples prefer stricter bankruptcy than singles?**
No divorce	No
No economies of scale	No
No divorce, no economies of scale	No
Couples have single expenses	No
Couples only one single expense	No
No scale, only one single expense	No
No divorce, only one single expense	Yes

Table 2.5: Decomposition Exercises

Notes: "Couples have single expenses" refers to the experiment where the calibrated expense process for married individuals is replaced by the one for singles. "Couples only one single expense" refers to the experiment where additionally couples are subject to only one expense process instead of two.

Figure 2.11: Fraction of Defaulters around Divorce Event



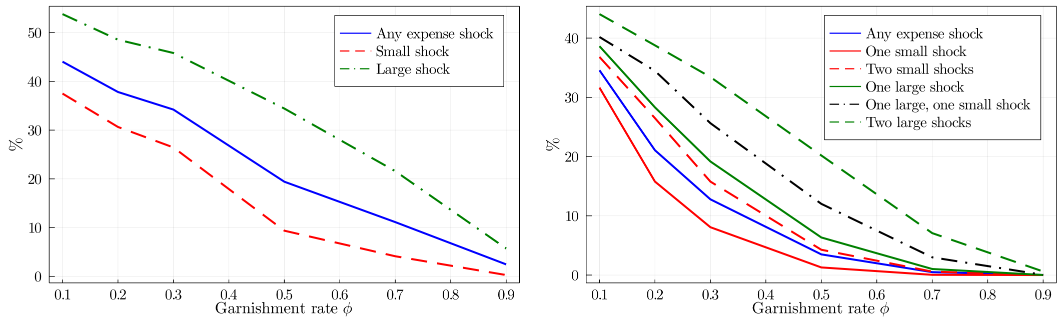
Notes: Event time denotes the time relative to the divorce event. The divorce event happens at time 0.

shock (red, solid line in right figure) drops strongly when garnishment rates increase from 0.1 to 0.2 (a drop of around 50%) or from 0.1 to 0.3 (a drop of around 75%). Compared to this, the fraction of single households that default after suffering a small expense shock (red, dashed line in left figure) only drops by around 18% when the garnishment rate increases from 0.1 to 0.2 or by around 29% when the rate increases from 0.1 to 0.3.[45] These results suggest that for couples garnishment rates higher than 0.1 quickly limit the usefulness of default to insure against smaller expense shock realizations. As couples get hit by at least one expense shock more often than singles, this makes lenient bankruptcy

[45]Similarly, going from the baseline to a garnishment rate of 0.1 the default rate for singles increases by a factor of 3.8, while it increases by a factor of 8.1 for couples.

Figure 2.12: Fraction of Defaulters cond. on Receiving Expense Shock

(a) Singles (b) Couples



Notes: This figure illustrates the fraction of households that default after receiving a certain combination of expense shocks.

regimes relatively more attractive to couples than singles.

2.7 Further Robustness Checks

One concern might be that the welfare result in Figure 2.5 is driven by how I model the cost of bankruptcy. Recall from Section 2.4.1 that in case of default a fraction ϕ of a household's wage is garnished. In particular, for couples the labor income of both spouses is garnished. Could couples prefer a lower garnishment rate than singles simply due to larger income losses for a given rate?

To examine this possibility, I change the bankruptcy cost from wage garnishment to a fixed cost. To be precise, the budget constraint in case of default now looks as follows for singles:

$$c \leq (e_j \cdot z_g \cdot n) - \phi$$

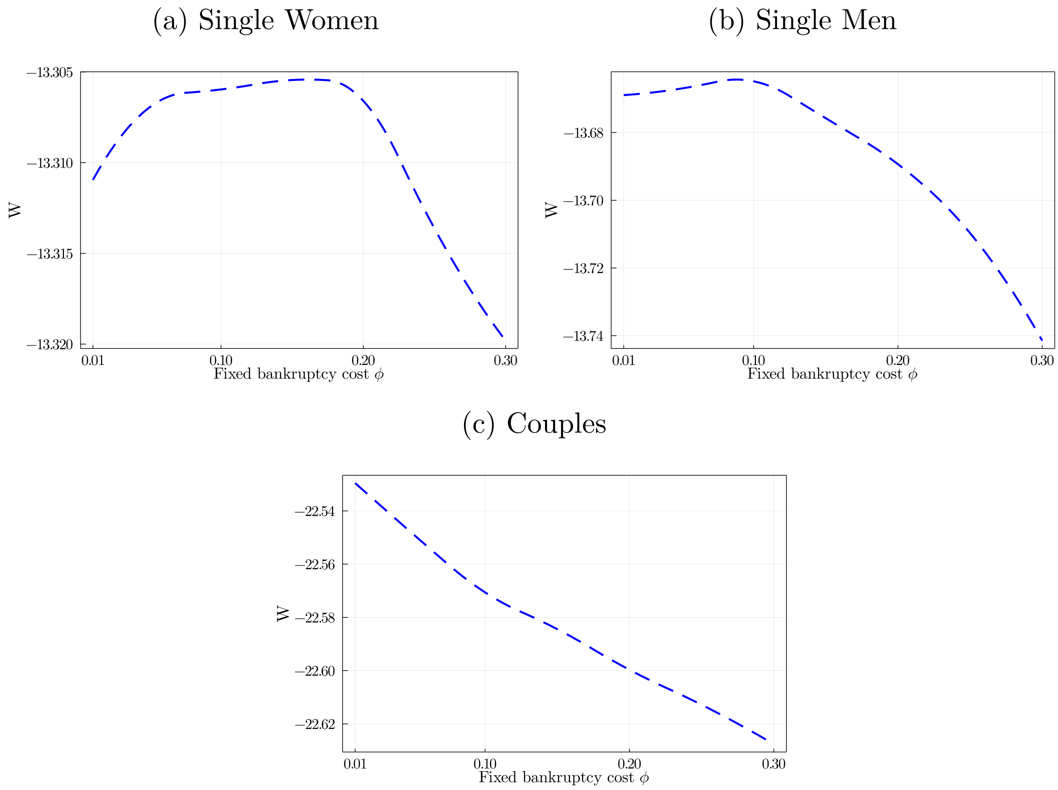
And for couples:

$$c \leq (e_j \cdot z_f \cdot n_f + e_j \cdot z_m \cdot n_m) - \phi$$

This means that the absolute costs of bankruptcy are now identical for single and couple households. I then vary the bankruptcy cost ϕ from 0.01 to 0.3.[46]

[46]Note that for a fixed bankruptcy cost, it is only possible to solve the model for ϕ up to around 0.3 in my calibration. Beyond that empty budget sets start to appear: In certain states it is impossible for households to either repay or default, as both choices will lead to

Figure 2.13: Welfare - Fixed Bankruptcy Cost



Notes: The welfare measure W is defined in Equation (2.21). In this experiment the proportional wage garnishment cost of bankruptcy is replaced by a fixed cost that is the same for singles and couples.

Figure 2.13 illustrates that the previous welfare results still hold in this case. Again, couples prefer a more lenient bankruptcy regime compared to singles.

2.8 Conclusion

Bankruptcy rates in the U.S. differ strongly across marital status. In particular divorce has been shown to be an important driver of household bankruptcies. However, until now the quantitative consumer default literature has ignored differences in marital status. Work in this literature models all households as a single entity. In this paper, I address this gap and investigate how household marital status affects the welfare implications of bankruptcy regulation. To do

non-positive consumption. With proportional wage garnishment this can never happen as it is always possible to default.

so, I build a consumer default model that is the first to explicitly model both single and couple households. In addition, my model also allows for couples to divorce.

Using a calibrated version of my model I examine the welfare effects of different degrees of bankruptcy leniency for singles and couples separately. I find that there are large differences between these two types of households in my model: Couples prefer a more lenient bankruptcy regime compared to singles. I show that this finding is driven mainly by differences between couples and singles on the income and expense sides as well as divorces. In terms of the income side the main distinction is that couples have access to intra-household insurance whereas singles do not. I show that this difference in fact makes couple prefer a stricter bankruptcy regime than singles. However, in contrast to singles couples can also be divorced. Furthermore, couples suffer expenses more often as there are two individuals. These two factors make default more valuable to couples relative to singles and their influence outweighs the income side. The net effect is then that couples prefer a more lenient bankruptcy regime than singles. To summarize, my results suggest that ignoring household heterogeneity across marital status in consumer default models may not be an innocuous choice for welfare analysis and thus policy experiments.

One natural extension of the model would be to endogenize the divorce decision of couples.[47] In the current model, a couple may get divorced even when one spouse would be badly off after divorce. On the one hand, in a model with endogenous divorce such a spouse may instead choose to compensate his/her partner by adjusting the allocation of resources within marriage. This could lessen the need for bankruptcy after divorce and make couples prefer a stricter bankruptcy regime. On the other hand, endogenous divorce may increase precautionary savings of couples as illustrated in Doepke and Tertilt (2016). This increase would make the higher interest rates for borrowing associated with more lenient bankruptcy regimes less costly.

Another promising avenue for future research could be to allow for separate asset holdings in couple households. This extension would enable researchers to model separate bankruptcy filings within couples.[48] Separate asset holdings

[47] Endogenous divorce can be modeled in a limited commitment and endogenous bargaining framework such as Voena (2015).

[48] As a result, common law states can be sensibly modeled in such a framework. See also Section 2.3.

could lead to interesting situations where couples allocate assets and debt strategically. For instance, couples may allocate less debt/more savings to the spouse who would be worse off in divorce.[49] This allocation could make bankruptcy after divorce less important.

It could also be interesting to include marriage in the model. This addition could help the model to better match the data. Adding an exogenous marriage shock would be relatively straightforward. Such a change could make singles prefer a more lenient bankruptcy regime than in the current baseline, as they anticipate turning into a couple household later in life. At the same time, the prospect of marriage may also change the behavior of singles. They may want to borrow more in younger ages as they count on benefiting from economies of scale in consumption later in life as a couple. More borrowing could make singles prefer a stricter bankruptcy regime with lower interest rates.

A further interesting angle could be to examine this model through the lens of gender equality. The empirical literature has highlighted that it is often women with children who end up in precarious financial situations after divorce. Extending the model in this paper by adding children and childcare would allow researchers to model this problem as well as search for policy interventions in the bankruptcy law space that could alleviate this issue.

[49] Separate assets would require the researcher to specify how assets are divided upon divorce. One possibility is title-based distribution under which assets are divided according to the title of ownership. Another option is equitable distribution.

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Appendix

2.A Computational Details

Variable	Symbol	# Points	Range
Wage processes			
Women	z_f	5	$\{0.42, 0.64, 1.0, 1.55, 2.41\}$
Men	z_m	5	$\{0.33, 0.58, 1.0, 1.73, 2.99\}$
Lifecycle productivity profile	e_j	16	$\{0.77, 0.82, ..., 1.01, 0.95\}$
Initial distribution of newborn wage		5	$\{0.2, 0.2, 0.2, 0.2, 0.2\}$
Expense shocks	κ	$3{\times}2 \times 16$	
Assets	a	240	$[-5.0, 13.0]$
Labor choice	n	3	$\{0, 0.5, 1\}$

Table 2.A.1: Grids Used for Model Computation

Notes: Expense shocks differ across marital status (single vs. married) and age (16). In each subgroup there are three possible expense shock realizations.

Table 2.A.1 summarizes the computational grids used in the solution of the model. The grids for the wage processes are discretized into two 5-state Markov processes using the Rouwenhorst method. The asset grid is equally spaced with 100 grid points in the negative space and 140 points in the positive one. The asset grid is chosen sufficiently wide such that no household will ever pick a point on the boundary of the grid.

I solve the model backwards. Starting in the final period of life, I first compute the value functions for singles, divorced, and couples. Note that households are not allowed to die with debt. Thus, I do not need the loan pricing functions to solve for the value functions in the final period. Using the computed value functions I can derive the repayment choice for every state. I can use these choices to compute repayment probabilities which in turn give me the loan pricing schedules in the second-to-last period. Using these pricing functions I can again compute the value functions in this period. I iterate this procedure backward until I reach the first period of life.

2.B Expense Shock Estimation Details

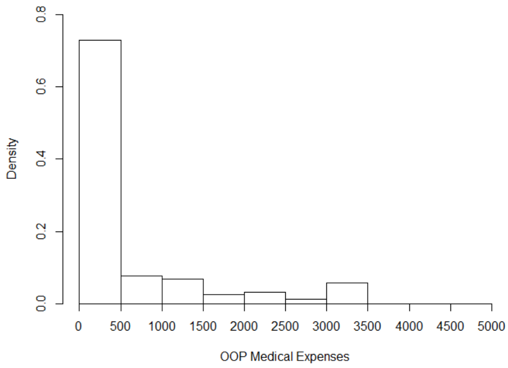
Figure 2.B.1 depicts histograms of annual out-of-pocket medical expenses as reported in MEPS 2019 for single and married individuals across different age groups.[50] I winsorize the top 5% of observations in each subgroup.

Figure 2.B.2 depicts the distribution of bad medical debt across age for singles/divorced and married. More specifically, I plot the difference in charges versus expenditures for 2019: $(charge_i^{2019} - exp_i^{2019})$ in Equation (2.19). One can see that single individuals have more bad debt than married ones in the age groups 44-49 and 56-61. Note that I winsorize the top 5% of observations in each subgroup.

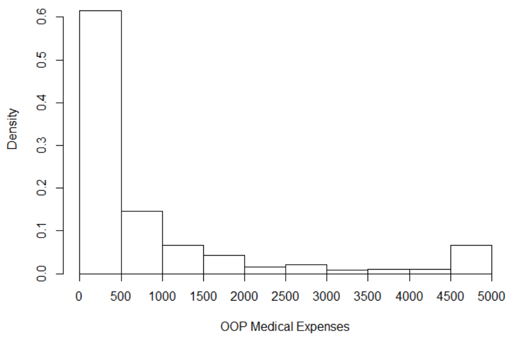
[50]Note that these expenses are the out-of-pocket expenses as recorded in MEPS 2019 (adjusted for consistency with aggregate data). They do not include estimated bad debt.

Figure 2.B.1: Histograms of Out-of-Pocket Expenses (in 2018 US-Dollars)

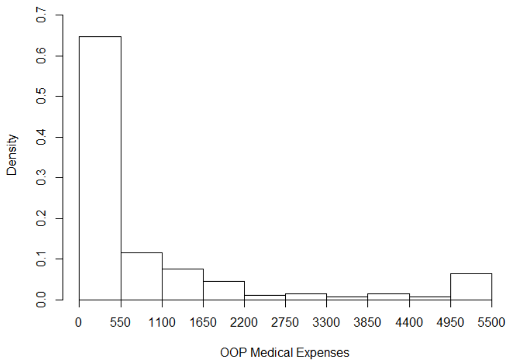
(a) Singles Aged 32-37



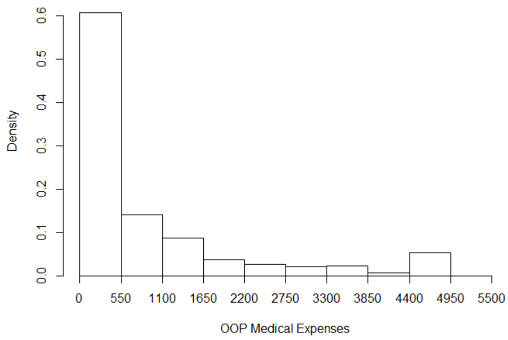
(b) Married Aged 32-37



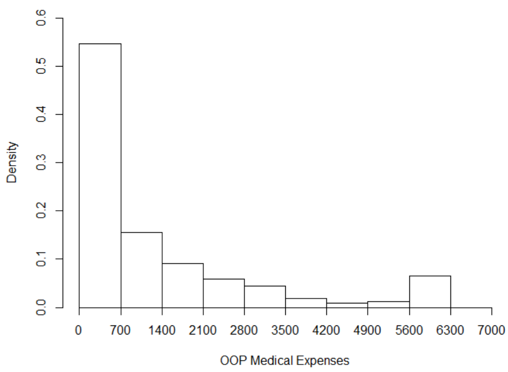
(c) Singles Aged 44-49



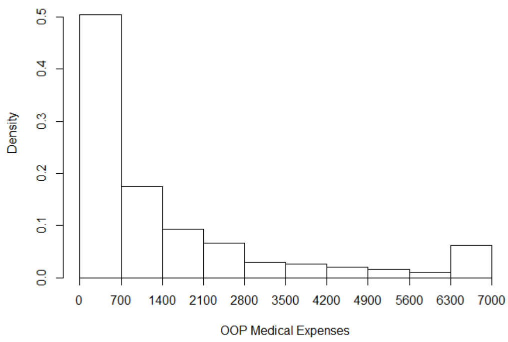
(d) Married Aged 44-49



(e) Singles Aged 56-61



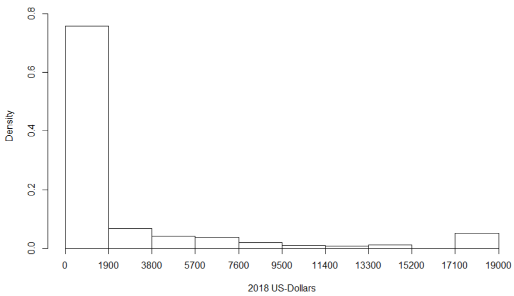
(f) Married Aged 56-61



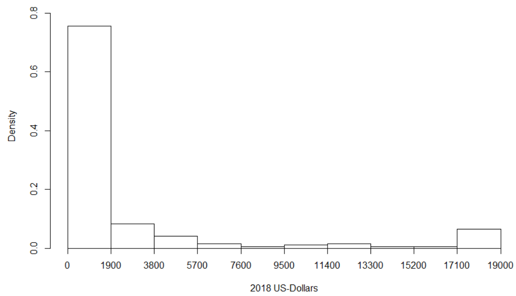
Notes: Source: MEPS (2019). The top 5% of observations in each subgroup are winsorized.

Figure 2.B.2: Histograms of Individual Bad Debt

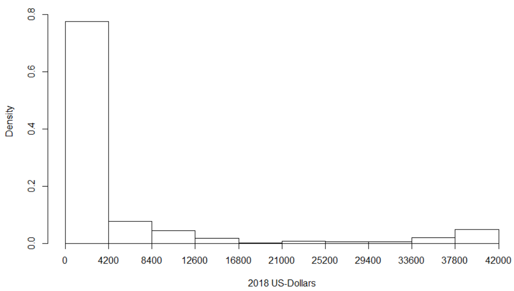
(a) Singles Aged 32-37



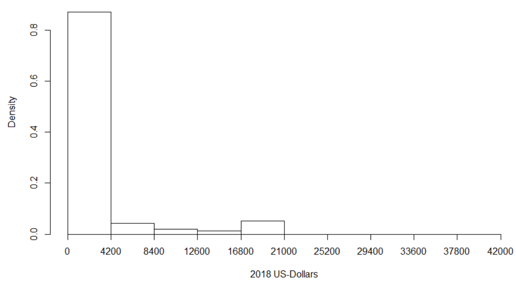
(b) Married Aged 32-37



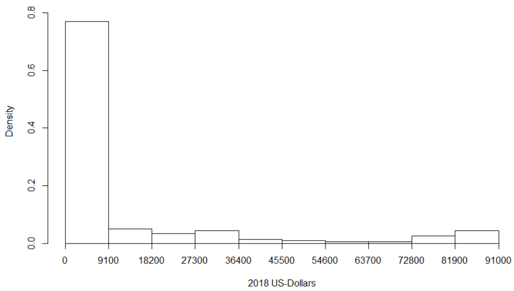
(c) Singles Aged 44-49



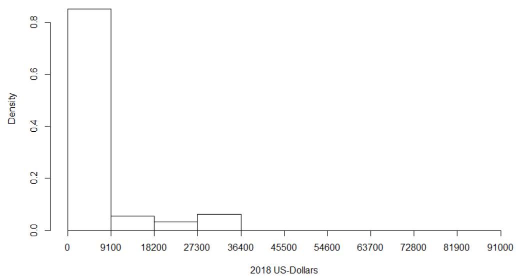
(d) Married Aged 44-49



(e) Singles Aged 56-61



(f) Married Aged 56-61



Notes: Source: MEPS (2019). Bad debt is measured as the difference between total charges and total expenditures. See also Equation (2.19). The top 5% of observations in each subgroup are winsorized.

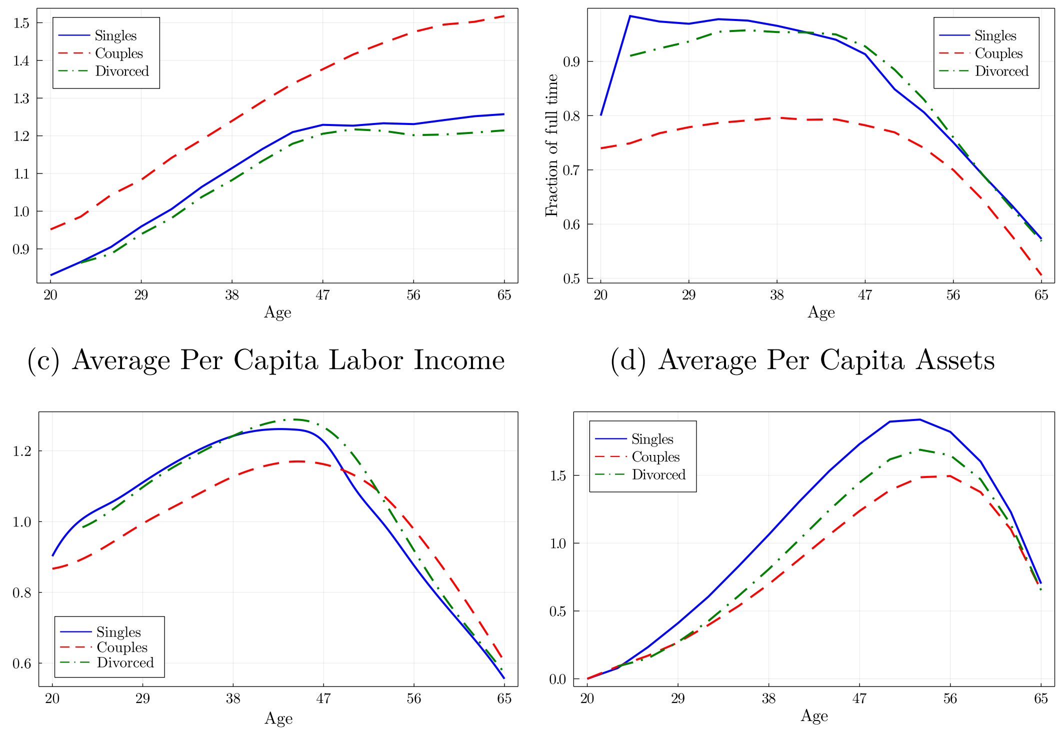
2.C Additional Results

Figure 2.C.1 depicts lifecycle profiles of average per capita consumption, labor supply, income and assets in the baseline model. Figure 2.C.2 shows interest

Figure 2.C.1: Model Lifecycle Profiles

(a) Average Per Capita Consumption (b) Average Per Capita Labor Supply

(c) Average Per Capita Labor Income (d) Average Per Capita Assets



Notes: Since my model has a period length of three years, the x-axis denotes 3-year age brackets.

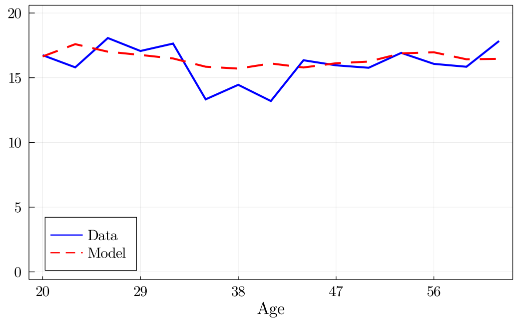
rates across age and marital status in the baseline model as well as in the data.

In Figure 2.C.3 I show the welfare results for the counterfactual in which, starting from the baseline, I assume that the expense shock processes within couples are perfectly correlated. We can see that couples prefer the most lenient bankruptcy regime in this case.

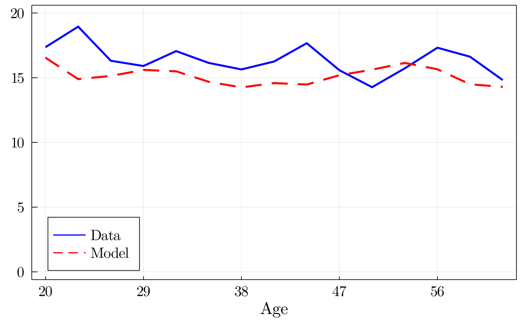
In Figure 2.C.4 I plot the welfare results for married women and men individually across garnishment rates ϕ. I compute the value of individuals within couples by taking the optimal consumption, labor, asset and default policy functions derived from the couples' problem as given. Let $c^* \equiv c^*(a, z_f, z_m, \kappa_f, \kappa_m)$, $a^* \equiv a^*(a, z_f, z_m, \kappa_f, \kappa_m)$, and $l_g^* \equiv l_g^*(a, z_f, z_m, \kappa_f, \kappa_m)$ denote these policy functions. Use $V_{C,j}^g$ to denote the value of a married individual with gender g and age j.

Figure 2.C.2: Interest Rates Across Age

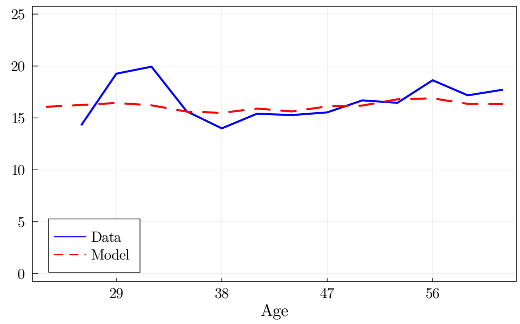
(a) Singles



(b) Couples



(c) Divorced



Notes: Source for data: SCF 2019. Since my model has a period length of three years, the x-axis denotes 3-year age brackets.

The value is then given by:

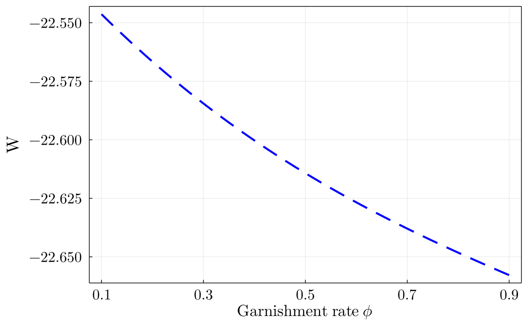
$$V^g_{C,j}(a, z_f, z_m, \kappa_f, \kappa_m) = u\left(\frac{c^*}{\eta}, l^*_g\right)$$
$$+ \beta \cdot \Bigg((1-\psi)\cdot \mathbb{E}_{z'_f, z'_m, \kappa'_f, \kappa'_m}\left\{V^g_{C,j+1}(a^*, z'_f, z'_m, \kappa'_f, \kappa'_m)\right\}$$
$$+ \psi \cdot \mathbb{E}_{z'_g, \kappa'_g}\left\{V_{Div,g,j+1}(\frac{a^*}{2}, z'_g, \kappa'_g)\right\}\Bigg)$$

To measure the welfare of individuals within couples, I again use ex-ante well-being:

$$W^g_C = \mathbb{E}_{z_f, z_m}\left\{V^g_{C,j=0}(a=0, z_f, z_m, \kappa_f = 0, \kappa_m = 0)\right\} \tag{2.22}$$

where W^g_C denotes the ex-ante value of a married individual with gender g.

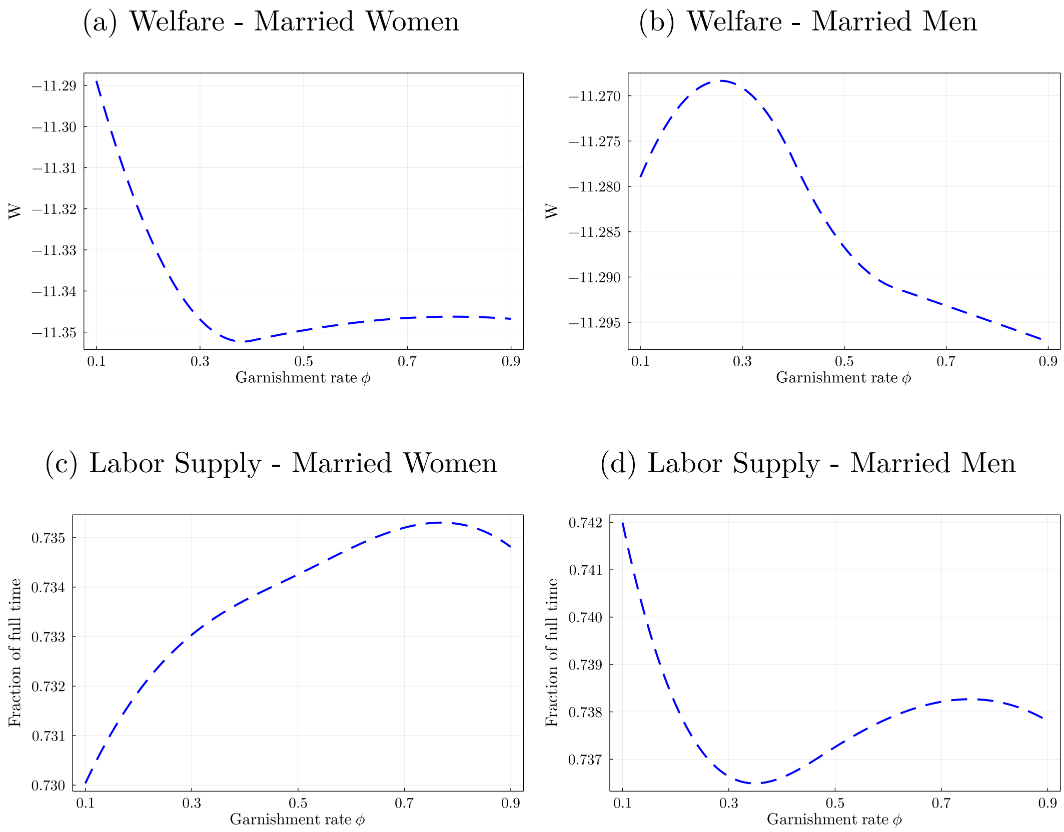
Figure 2.C.3: Welfare of Couples - Perfectly Correlated Expenses



Notes: The welfare measure W is defined in Equation (2.21). In this experiment the expense shock processes within couples are assumed to be perfectly correlated.

In Figures 2.C.4a and 2.C.4b we can see that married women prefer a more lenient bankruptcy regime than married men. This result is driven by differences in female and male labor supply across garnishment rates as shown in Figures 2.C.4c and 2.C.4d.

Figure 2.C.4: Within Couple Results



Notes: The welfare measure W is defined in Equation (2.22). These plots show the results for individual welfare and labor supply of married women and men.

Eidesstattliche Erklärung

Hiermit erkläre ich, die vorliegende Dissertation selbstständig angefertigt und mich keiner anderen als der in ihr angegebenen Hilfsmittel bedient zu haben. Insbesondere sind sämtliche Zitate aus anderen Quellen als solche gekennzeichnet und mit Quellenangaben versehen.

Mannheim, 27.06.2022

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