Credit and Welfare Effects of Interchange Fees and Credit Card Rewards

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Abstract

In most countries, merchants accepting credit card payments pay a percentage of the transaction amount as a fee to the credit card network. A portion of this fee, known as the interchange fee, is paid to the cardholder's bank. For reward cards, most interchange fees are returned to the cardholder as cashback, miles, or points. For nonreward cards, the interchange fee could be used to make contract terms more generous. We use a heterogeneous-agent macro model augmented with a competitive credit card industry to understand the credit implications of credit card rewards and interchange fees. We find that rewards and interchange fees substantially expand credit limits and lower interest rates. A policy permitting a modest interchange fee but prohibiting rewards is welfare-improving because, in a competitive environment, the fee induces higher credit limits and lower interest rates, which benefit all borrowers.

Keywords: Credit card rewards, interchange fee, credit limits, interest rates, defaults, welfare

JEL Codes: D15, E44, G51

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1 Introduction

In the United States, merchants who choose to accept credit cards for payments pay a fee that can range between 1.5 and 3.5 percent of the transaction value. This fee is shared between the merchant's bank, the cardholder's bank, and the credit card network provider (such as Visa or Mastercard). A major portion of the overall fee, called the interchange fee, goes to the cardholder's bank, and most of it is used to make the credit card more attractive to the cardholder. For instance, for so-called reward cards, 90 percent of the interchange fee is given out to the cardholder in the form of cash, points, or miles.[1] While nonreward cards do not feature such benefits, the interchange fee could be used to make the card attractive in other ways. In this paper, we attempt a quantitative-theoretic evaluation of the effects of interchange fees and rewards on credit card contract terms, namely, interest rates and credit limits, and the consequent impact of fees and rewards on household welfare.

Our quantitative model implies that reward programs funded by interchange fees increase credit limits and lower interest rates. This is because the loss of rewards upon default makes defaulting on reward cards less attractive and, therefore, rewards are a force in favor of higher limits and lower interest rates. In turn, a higher limit makes a reward card more attractive by increasing the payment capacity of the card so that more purchases can potentially earn rewards. Interchange fees not given out as rewards — retained interchange fees — are also a force for higher limits and lower interest rates. This is because retained interchange fees are a source of pure revenue for a card company, and they compete for it by offering higher credit limits and lower interest rates on nonreward cards. In other words, retained interchange fees act like a subsidy to credit card borrowing.

These effects are established in a model that quantitatively captures the main patterns in credit terms, credit use, and default rates observed for reward and nonreward cards in high-quality administrative data.[2] The model is a canonical heterogeneous-agent macro model augmented with a competitive credit card industry (Chatterjee and Eyigungor (2025)) which we extend to have two types of credit cards, reward and nonreward. The model's retail sector is competitive and, as is the current typical practice, retailers do not set prices differentially for reward, nonreward or cash customers. Interchange fees are, thus, fully passed on to customers via a markup on retail prices.

As discussed below, the distributive effects of the interchange fees and their optimal size are topics of interest in the interchange fee literature. We complement the literature by

[1] See https://www.consumerfinance.gov/data-research/research-reports/the-consumer-credit-card-market/.

[2] We use the Board of Governors Y-14M data. See Appendix A for details.

examining the welfare effects of interchange fees that flow from their credit effects. Specifically, we compute the welfare effects of a move from an economy in which there are credit cards but no interchange fees to the current situation with interchange fees and reward and nonreward cards. Since reward cardholders get rewards that retailers finance by a general increase in prices, we would expect them to be better off. But they are also better off because rewards expand credit limits and lower interest rates.

We also find that the move benefits nonreward cardholders significantly. This gain stems from the fact that interchange fees subsidize credit card borrowing via higher limits and lower interest rates. But why is subsidizing credit good? The reason is that people in our model are estimated to be impatient and would like to borrow more. However, they are constrained because they cannot pledge future income to repay their debts. But if retailers pay a percentage fee to card companies on purchases, which they finance by charging customers higher prices, then, in effect, nonreward cardholders are pledging a portion of their future income to card companies. In turn, competitive card companies use the pledged income to offer welfare-improving credit terms.

The benefit of interchange fees passed back to cardholders as better credit terms suggests that even reward cardholders might prefer a world in which rewards are prohibited and the interchange fee is used to subsidize credit. Indeed, we show that moving from a situation with no interchange fees (and rewards) to one in which the interchange fee is a modest 0.5 percent but rewards are prohibited is better for all consumers than the current situation. For reward cardholders, the subsidy more than offsets the loss of rewards and for nonreward cardholders, the modest interchange fee leads to lower retail markups.

There are no prior studies that examine the interaction between rewards programs and the terms offered on revolving debt. Fulford and Schuh (2024) models the payments and revolving debt uses of a credit card, but they do not explore the impact of rewards or interchange fees on credit limits or interest rates. Earlier Chakravorti and To (2007) tackled, in a stylized model, the question of why credit card payments were costlier than cash or checks and argued that the option to revolve increased sales and profits for merchants and card issuers bargained away the additional profits via higher processing fees. But the connection between rewards and credit terms was not explored in their paper.

Credit cards have been controversial as a means of payment because merchants typically do not price goods differentially depending on the payment instrument used for the purchase. This means merchants partially recoup payment costs by passing them on to consumers at higher retail prices. Schuh, Shy, and Stavins (2010) calculated the subsidy entailed from cash

to credit card users and found that, given the pattern of payment instrument choice across the income spectrum, credit card payments resulted in a net transfer of income from the poor to the rich. Felt, Hayashi, Stavins, and Welte (2020) revisited this calculation, taking into account rewards on both credit and debit cards and fees associated with the use of credit cards and bank accounts, and found, once again, that higher income individuals benefited at the expense of lower income individuals. Our model has a similar income redistribution from poorer to richer individuals and from impatient to patient people. Rewards increase prices for everyone, but the impatient and the poor borrow on their cards and, so, have less capacity to pay for consumption using their credit cards and hence earn fewer rewards.

A novel insight of our model is that if card companies charge merchants an interchange fee, but rewards are prohibited, welfare can be higher for everyone. To place this result in context, note that there is considerable debate concerning the optimal level of interchange fees and whether competition will lead to a socially optimal level. However, this debate (Schmalensee (2002) and Rochet and Tirole (2003), among others) focuses exclusively on the payment feature of credit cards and ignores the fact that it is also a vehicle for unsecured consumer loans. In a competitive world, we expect the interchange fee revenue to be passed on to cardholders as rewards or more generous credit terms. In either case, our paper shows that the credit effects are substantial and generally welfare-improving. The reason for this is that the unsecured credit market labors under a severe constraint — the inability of cardholders to commit to repay their loans — and this friction is alleviated by rewards and interchange fees financed by a "tax" (markup) on retail goods.

The paper is organized as follows. In section 2 we describe the main facts regarding reward and nonreward cards. In Section 3 we present the model. In Section 4, we use some of the facts from Section 2 to calibrate the model and use others to validate it. Following the quantification of the model, Section 6 discusses how rewards and interchange fees impact credit terms and welfare. Section 7 presents our policy counterfactual wherein the interchange fee is reduced to a modest 0.5 percent and rewards are prohibited.

2 Terms, Usage, and Performance of Reward and Nonreward Cards

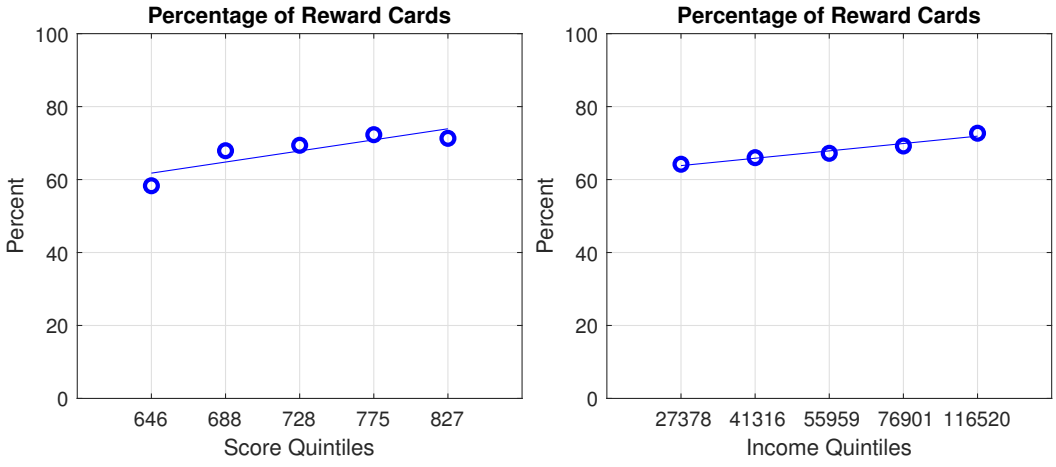
We use the Board of Governors Y-14M reports to develop facts on reward and nonreward cards.[3] We use a 1-in-200 random sample of all new, revolving, general purpose, and unse-

[3]This data is collected by the Board of Governors of the Federal Reserve System as part of the annual comprehensive capital analysis and review (CCAR) of large U.S. bank holding companies with assets greater than $50 billion as mandated by the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act. One part of this data (Y-14M) reports on the terms, usage, and performance of individual credit card accounts managed by the reporting banks. The data covers about 80 percent of all U.S. credit card accounts in existence at a point in time.

cured credit-card accounts originated between June 2014 and May 2015 with one primary account holder.[4] Following the initial random selection, the sample was trimmed for outliers[5] and, in preparation for the quantitative theory developed in the paper, it was truncated in two ways. First, in order to align the distribution of reported annual incomes with the distribution implied by estimated earnings processes commonly used in calibrated macro models, accounts with annual incomes in the top or bottom 7 percent of the distribution of reported incomes-at-origination were removed. And, second, for reasons of computational tractability, accounts with credit scores below 620, comprising the bottom 13.7 percent of the credit-score-at-origination distribution, were also removed.[6]

We classified accounts that give back cash, miles, or points as a reward card and those that do not offer any type of rewards as a nonreward card. Figure 1 displays the share of cards that have rewards by credit score at origination (left panel) and by income at origination (right panel). In each figure, a dot corresponds to the mean value for a quintile. The plotted lines are lines of best fit through these dots. Generally, 60 percent or more of newly issued cards are reward cards, and their share is modestly increasing in both credit score and income.

Figure 1
Share of Cards with Rewards by Score & Income Quintiles



[4]We chose our sample period to minimize changes in the bank prime rate as the majority of credit cards specify contractual interest rates as a spread ("margin") over (usually) the bank prime lending rate and we don't model changes in the prime rate. The prime rate was constant during 2011-2015.

[5]We excluded accounts for which reported borrower annual income was less than $1000 (most likely students) and credit-score-at-origination was less than 100 (most likely a reporting error);we also excluded accounts for which credit-limit-at-origination was less than $100.

[6]The average scores of those so excluded is 593 which is well inside the score band of 580−619 commonly designated as the "subprime" category of borrowers. To explain the terms and performance of these most risky accounts would require modeling additional heterogeneity which would increase computational burden from an already high level.

Turning to contract terms, we measure an account's credit limit as the ratio of the account's credit limit as observed 18 months following origination to the cardholder's reported income at origination. Thus scaled, credit limits are strongly increasing in credit score and decreasing in income for both reward and nonreward cards as shown in Figure 2. Importantly, scaled credit limits are, on average, about 30 percent higher for reward cards regardless of whether we look at accounts by scores or by incomes.

Figure 2
Credit Limit to Income Ratio by Score & Income Quintiles

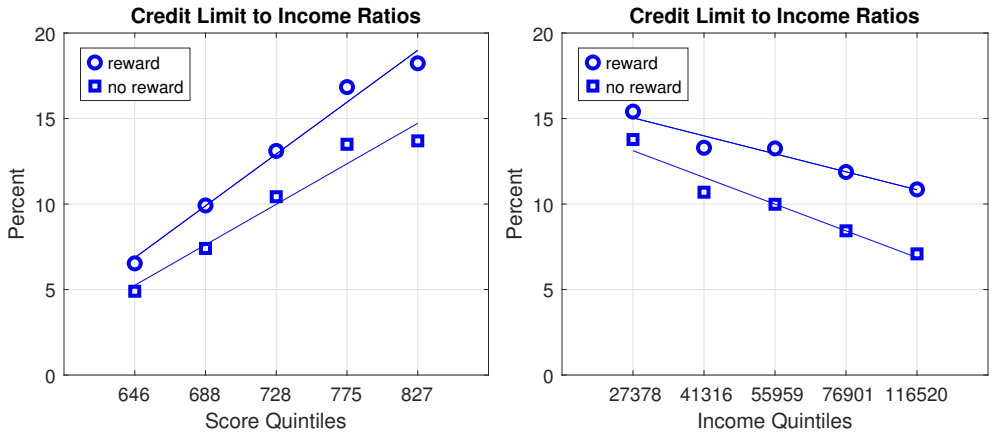
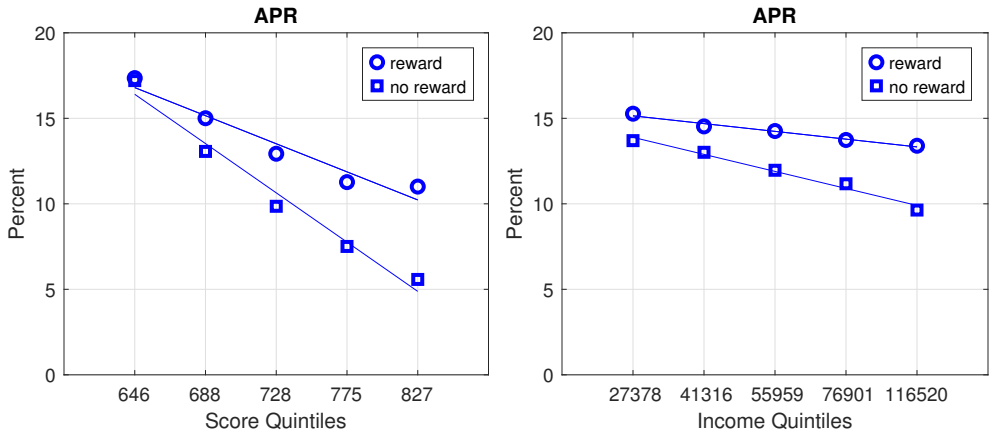


Figure 3
APR by Score & Income Quintiles



Interest rates are harder to measure given that promotional interest rates may apply on revolving balances in the beginning of the credit card contract and people may move revolving balances to cards with promotional rates. To obtain a measure of effective interest rates, we compute a balance-weighted average of promotional and nonpromotional interest rates each month and compute the average of these monthly interest rates over the 60 months

following origination.[7] Figure 3 shows that effective interest rates decline strongly with scores and decline moderately with incomes for both reward and nonreward cards. Importantly, interest rates on reward cards are generally higher than the interest rate on nonreward cards, with the gap rising with scores and incomes.

Figure 4
Default Frequency and Utilization by Score & Income Quintiles

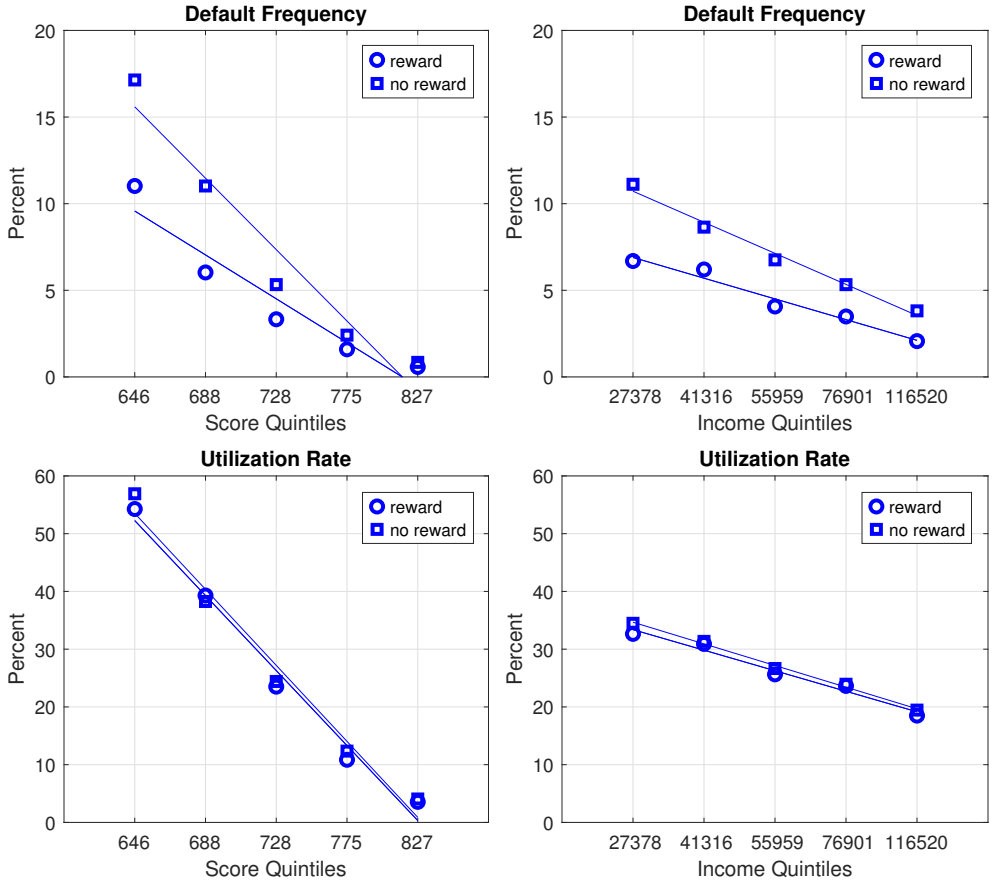


Figure 4 displays the performance patterns of credit card accounts. We focus on two measures of performance. One is the frequency of default. We define an account to be in default if one of the following has occurred within 24 months of origination: (i) The account is reported to be in a debt waiver or in bankruptcy, or (ii) the account is reported 120 days or more past due and the delinquency is not cured in the following 6 months.[8] The second

[7] In computing the time average, we make two further adjustments. First, we deflate all future balances (promotional or not) by CPI inflation, with June 2014 as the base. Second, contract interest rates on cards change with changes in the bank prime rate. Since our theory abstracts from changes in the risk-free rate, we add or subtract a time-period-specific constant from monthly averages so that the average of all interest rates in each month is the same as the average interest in June 2014.

[8] A delinquency is cured if the account is not classified as delinquent and does not transition into one of the categories mentioned under (i) in the next 6 months.

measure is the utilization rate of the card for which we use the ratio of revolving debt to credit limit at 24 months following origination.

The top panels display the variation in frequency of default. Default frequency is strongly related to credit score. For nonreward cards, the default frequency in the bottom quintile of scores is about 15.1 percent while it is 0.5 percent for the top quintile. For reward cards, the default frequency in the bottom quintile of scores is about 10.8 percent while it is 0.4 percent for the top quintile. The default rates are lower for reward cards and that is especially pronounced for the lowest credit score bin, where default rate is a third lower for the reward cards. Default frequencies also decline with income but the variation is less pronounced. Default rate is around 25 percent lower for reward cards for all income bins.

The bottom panels display the ratio of revolving balances to credit limits. The utilization rate is strongly decreasing in credit score for both reward and nonreward cards. Utilization is also decreasing with respect to income, but the decline is less pronounced. Utilization rate is almost the same for reward and nonreward cards conditional on the credit score and income bins.

The patterns displayed in Figures 1 to 4 are the facts we focus on in this paper.

3 Model

Time is discrete. We will describe the model in recursive notation so variables, such as y_t and y_{t+1}, will be denoted as y and y'.

An individual's income in a period is $P \cdot [y + m]$, where $P > 0$ is a time-invariant permanent component, $y > 0$ is a discrete persistent component that evolves according to a first-order Markov chain $F(y'|y)$, and m is a continuous transitory component drawn each period from a uniform distribution with support $[-\lambda y,\ \lambda y]$, $\lambda \in (0, 1)$.

An individual's preference is a discounted sum of period utilities, where the period utility function is CRRA with curvature parameter $(1 - \gamma)$, $\gamma > 0$. An individual survives from one period to the next with a constant probability $\nu \in (0, 1)$.

There are I types people, with a type denoted $i \in \{1, 2, \ldots, I\}$. The measure of each type is $\mu^i > 0$. Types differ in their discount factor β, default cost ϕ, and whether they are eligible for a reward card or not. A person of type i is, thus, a triple $(\beta^i, \phi^i, \chi^i)$, where χ is 1 if the individual is a reward type and 0 otherwise. We also permit individuals to vary by the permanent income component P, so an individual is indexed by $\{i, P\}$.[9]

[9] In principle, P could be another dimension of type, with a type as the quadruple $\{P^i, \beta^i, \phi^i, \chi^i\}$. However, the equilibrium of the model will have the property that all decision rules scale with P, so there will be no need,

A credit card is an exclusive contract between a card company and an individual. It is defined by the pair $(\underline{a}, R)$, where $\underline{a} < 0$ is the credit limit on the card and $R > 0$ is the (gross) interest rate at which the individual can revolve balances on the card. Individuals can also make payments using their cards and, importantly, the credit limit also constrains the total spending that can be funneled through a card in a given period: Purchases using the card as a means of payment cannot exceed the card's credit limit. A card's contract terms are fixed for as long as the individual holds the card. All individuals can save at the common risk-free (gross) interest rate R_f.

A credit card held by a reward-type receives a flow cashback from merchants equal to a fraction $\psi^R \in (0, 1)$ of the purchases made in that period using the card. There is a "cashback" rate ψ^{NR} for nonreward-types as well, but this flow is received by the credit card company, not the individual. The cashback rates ψ^R and ψ^{NR} are treated as parameters and apply to all reward and nonreward cards, respectively.

A person with a balance on her credit card has the option to default. If a type i person defaults, she loses her card and the card company seizes a fraction $0 < \phi^i \leq 1$ of her transitory income in excess of $-\lambda y$ in the period of default.[10] She is also prohibited from saving in the period of default and with probability $(1 - \delta)$ she is shut out of the credit card market in the period following default. In subsequent periods, conditional on being shut out, she continues in that state with probability $(1 - \delta)$.

A person who does not have a card and is not shut out of the card market searches for a card with probability $\eta > 0$. Search and its outcome happens before the transitory shock m is realized. As there is complete information, an individual who can search searches for contracts that are being offered to people of her type i, her persistent earnings y, her asset position a, and her permanent income component P. It costs a card company $\tau \cdot P$, $\tau > 0$, to post a contract in the $\{i, P\}$ market.[11] Card companies commit to the terms of posted contracts, if accepted. These assumptions makes our search environment one of directed search.

To generate active search, we assume that card holders get separated from their card with probability ξ. The separation shock occurs before the transitory shock m is realized. Upon separation, if she is not carrying a balance on her card, the individual searches for a

computationally speaking, to carry P around as a state. Furthermore, P need not be discrete, whereas all other dimensions of type must be discrete for computation. For both these reasons it is convenient, notation-wise, to separate P from i.

[10] The substantive assumption is that garnishment increases with income of the defaulter, which is reasonable. The specific form ensures a computationally tractable threshold rule for default: default is optimal for m below a cutoff.

[11] The assumption that contract posting costs is proportional to P ensures the scaling properties with respect to P noted in footnote 11

new card with probability η. If she has a balance on her card, the separation shock has no effect and she continues on with her card.

3.1 Decision Problems

Timeline of Events:

1. The period opens and the card separation shock, the persistent income y, and the exclusion shock for people in default are realized.
2. Card companies post contracts and people without cards who can search, search for a card; outcome of this search is realized.
3. The transitory shock m is realized.
4. Indebted individuals make their default decision.
5. Re-payers and non-indebted individuals make their consumption and asset decisions, cashback from card purchases are received by individuals and card companies and the period closes.

Individuals:

Let $h^i(a, y, m; P)$ denote the value of an $\{i, P\}$ individual who is not shut-out of the card market but failed to get a card in the current period. This could be because she could not search or she searched but failed to make contact. In this situation, she can only save. Let $S^i(a, y; P)$ denote the ex-ante value of an $\{i, P\}$ person in state (a, y) who is without a card but searching for one. The qualifier ex-ante means that this is an expected value prior to the realization of the transitory income shock m. Then $h^i(\cdot)$ solves:

$$h^i(a, y, m; P) = \max_{a' \geq 0} \frac{c^{1-\gamma}}{1-\gamma} + \nu\beta^i \mathbb{E}_{y'|y}\{\eta S^i(a', y'; P) + (1-\eta) H^i(a', y'; P)\} \tag{1}$$
$$z \cdot c = P \cdot [y + m] + R_f a - a' \text{ and } H^i(a, y; P) = \mathbb{E}_m h^i(a, y, m; P).$$

Here $z > 1$ is the markup imposed by merchants to recover the expense of the cashback given to individuals and card companies. It's value is determined in equilibrium.[12] The decision rules of this problem are denoted $c^i_h(a, y, m; P)$ and $a'^i_h(a, y, m; P)$.

[12] In principle, the markup could be varying over time which, in turn, would make value functions and decision rules time dependent. Such time variation can be handled, but to lighten the notation, it is not incorporated in the text.

Let $x^i(a, y, m; P)$ denote the value of a $\{i, P\}$ individual who is without a card and who is also excluded from the credit card market because of a past default. Such a person is also limited to saving and $x^i(\cdot)$ solves:

$$x^i(a, y, m; P) = \max_{a' \geq 0} \frac{c^{1-\gamma}}{1-\gamma} + \nu\beta^i \mathbb{E}_{y'|y} \left[\delta \left[\eta S^i(a', y'; P) + (1-\eta) H^i(a', y'; P)\right] + (1-\delta) X^i(a', y'; P)\right]$$
$$z \cdot c = P \cdot [y + m] + R_f a - a' \text{ and } X^i(a, y; P) = \mathbb{E}_m x^i(a, y, m; P). \tag{2}$$

The decision rules of this problem are denoted $c^i_x(a, y, m; P)$ and $a'^i_x(a, y, m; P)$.

Let $v^i(a, y, m; P, \omega)$ denote the value of a $\{i, P\}$ individual in state (a, y, m) who has a credit card with terms $\omega \equiv (\underline{a}, R)$. Then, v^i solves:

$$v^i(y, m, a; P, \omega) = \max_{a' \geq \underline{a}} \left\{ \frac{c^{1-\gamma}}{1-\gamma} + \nu\beta^i \mathbb{E}_{y'|y} W^i(a', y'; P, \omega) \right\} \tag{3}$$
$$z \cdot c = P \cdot [y + m] + Q(\omega) \cdot a - a' + \chi^i \cdot \psi^R \cdot \min\{3 \cdot L(a; \omega), \kappa \cdot z \cdot c\}, \text{ where}$$
$$Q(\omega) = \begin{cases} R(\omega) \text{ if } a < 0 \\ R_f \text{ if } a \geq 0. \end{cases}$$
$$L(a; \omega) = \begin{cases} -\underline{a}(\omega) & \text{if } a \geq 0 \\ [-\underline{a}(\omega) - R(\omega)(-a)] & \text{if } \underline{a} \leq R(\omega)a < 0 \\ 0 & \text{if } Ra < \underline{a}(\omega) \end{cases}$$

Here $L(a; \omega) \geq 0$ is the current period payment capacity of the card and is equal to the excess of the credit limit over inherited revolving debt (if any). The parameter $\kappa \in (0, 1)$ is the fraction of current period consumption that is eligible to paid via credit cards and is the same for all cardholders. If $\chi^i = 1$ (the individual is a reward type), rewards are earned on $\kappa \cdot z \cdot c$ up to $3 \cdot L(a; \omega)$. The factor 3 adjusts for the time period in the model being a quarter, while the billing/payment cycle of credit cards is a month.

For reasons of parsimony, we have refrained from modeling transactions balances, i.e., debt that results from new purchases made via credit cards and on which no interest is charged if it is repaid by the end of the following period (so-called "float"). Since the cash saved by using credit card for payments can earn interest or a convenience yield, the existence of "float" means that all cardholders (reward or nonreward) have a strict incentive to use their card for transactions to the fullest extent possible. With this in mind, we assume that cardholders funnel as much of their card-eligible purchases through their card as permitted by their (period-adjusted) credit limit.

For reward types it is optimal to make purchases on their cards to the maximum extent possible since they earn rewards. Nonreward types do not have reward reasons to use their credit cards for purchases, but we assume that for convenience reasons they too use their card for purchases to the maximum extent possible.

The function $W^i(a, y; P, \omega)$ is a $\{i, P\}$ card holder's ex-ante continuation value in the state (a, y) (to be given below). We let $a'^i_v(a, y, m; P, \omega)$ and $c^i_v(a, y, m; P, \omega)$ denote the associated (optimal) asset and consumption decision rules.

Let $v^i_{DEF}(y, m; P)$ denote the value of default to a $\{i, P\}$ person. Then,

$$v^i_{DEF}(y, m; P) = \frac{c^{1-\gamma}}{1-\gamma} + v\beta^i \mathbb{E}_{y'|y} \Big[\delta \left[\eta S^i(0, y'; P) + (1-\eta) H^i(0, y'; P)\right] + (1-\delta) X^i(0, y'; P) \Big].$$
$$z \cdot c = P \cdot [y - \lambda y + (1-\phi^i) \cdot [m + \lambda y]]. \tag{4}$$

In the event of default, the individual retains a fraction $(1-\phi^i)$ of her transitory income in excess of $-\lambda y$ and pays the rest to her creditors. We denote the consumption of defaulter as $c^i_d(y, m; P)$.

Letting $V^i(a, y; P, \omega)$ denote $\mathbb{E}_m v^i(a, y, m; P, \omega)$, the recursion for $W^i(a, y; P, \omega)$ is

$$W^i(a, y; P, \omega) = \begin{cases} \xi S^i(a, y; P) + (1-\xi) V^i(a, y; P, \omega) & \text{if } a \geq 0 \\ \mathbb{E}_m \left[\max\left\{v^i(a, y, m; \bar{\omega}^i_y(P)), v^i_{DEF}(y, m; P)\right\}\right] + & \\ \quad \mathbb{E}_m \left[\max\left\{v^i(a, y, m; P, \omega), v^i_{DEF}(y, m; P)\right\}\right] & \text{if } a < 0. \end{cases} \tag{5}$$

Let $d^i(a, y, m; P, \omega)$ denote the default decision rule: It is 1 if $v^i(a, y, m; P, \omega) < v^i_{DEF}(y, m; P)$ and 0 otherwise.

Finally, we can specify the recursion for $S^i(a, y; P)$. Let $f^i(\omega; a, y; P)$ denote the probability of an individual with characteristics $\{i, a, y, P\}$ encountering a contract ω. The individual takes this contact probability function as given. Let $\Omega^i(a, y; P) \equiv \{\omega \in R_- \times R_+ \,|\, f^i(\omega; a, y; P) > 0\}$ be the space of contracts potentially available to an $\{i, P\}$ person in state (a, y). Then,

$$S^i(a, y; P) =$$
$$\max\left\{ \max_{\omega \in \Omega^i(a,y;P)} \left\{ f^i(a, y; P, \omega) \cdot [V^i(a, y; P, \omega) - H^i(a, y; P)] + H^i(a, y; P) \right\}, H^i(a, y; P) \right\}.$$

The inner max chooses the best contract from the space of available contracts and the outer max recognizes that the individual who can search has the option to not engage in search and get the value $H^i(a, y; P)$.

Credit Card Companies:

Card companies choose the contract terms to offer to people of different types in different individual states. Once a contract is accepted, the companies simply follow through on the terms until the individual separates from the card or defaults on it. We assume that companies opportunity cost of funds is R_f.

Denote the value to a company of a credit card contract ω held by an $\{i, P\}$ person in state (a, y, m) as $\pi^i(a, y, m; P, \omega)$ and denote $\mathbb{E}_m \pi^i(a, y, m; P, \omega)$ by $\Pi^i(a, y; P, \omega)$. Then,

$$\begin{aligned}\pi^i(a, y, m; P, \omega) = \; & d^i(a, y, m; P, \omega) \times \phi^i \cdot [m + \lambda y] \; + \; \left[1 - d^i(a, y, m; P, \omega)\right] \times \\ & \Big(- \min\{0, a\} \cdot R(\omega) + \min\{0, a'^i_v(a, y, m; P, \omega)\} \; + \\ & \quad [1 - \chi^i] \cdot \psi^{NR} \cdot \min\{3 \cdot L(\omega, a), \; \kappa \cdot z \cdot c^i_v(a, y, m; P, \omega)\} \; + \\ & \quad \frac{\nu}{R_f} \mathbb{E}_{y'|y} \Big[\left[1 - \xi \cdot \mathbb{1}_{\{a'_v \geq 0\}}\right] \Pi^i(a'^i_v(a, y, m; P, \omega), y'; P, \omega) \Big) \end{aligned}$$

If the individual is carrying a balance on the card and defaults, the card company gets $\phi^i[m + \lambda y]$ and the card ceases to exist. If she does not default, the card company receives the (gross) interest payment less new credit extended, if any. In addition, if the card is a nonreward card, the merchant cashback $\psi^{NR} \cdot \min\{3 \cdot L(\omega, a), \kappa \cdot c^i_v(a, y, m; P, \omega)\}$ is retained by the card company. Regardless of these inflows and outflows, the company gets the expected continuation value of the contract discounted by the risk-free rate. The expected continuation value takes into account that the card holder survives with probability ν and, if the cardholder is not revolving debt, the company loses the contract with probability ξ.

A card company chooses the profit-maximizing contract ω for an $\{i, P\}$ person in state (a, y). In making this choice, it takes the contact probability function $q^i(a, y; P, \omega)$ as given. The profit-maximizing contract solves:

$$\max_{\omega \in \Omega} q^i(a, y; P, \omega) \cdot \Pi^i(a, y; P, \omega) - \tau \cdot P$$

Let $\omega^{i*}(a, y; P, q^i)$ be a contract that attains the maximum. Then the net expected profit from posting a single $\omega^{i*}(a, y; P, q^i)$ contract is

$$N^{i*}(a, y; P, q^i) = q^i(a, y; P, \omega^{i*}(a, y; P, q^i)) \cdot \Pi^i(a, y; P, \omega^{i*}(a, y; P, q^i)) - \tau \cdot P$$

Let $e^i(a, y; P, q^i)$ be the measure of contracts $\omega^{i*}(a, y; P, q^i)$ posted by a card company to contact (and match with) a searching $\{i, P\}$ person in state (a, y). Then,

$$e^i(a, y; P, q^i) = \begin{cases} 0 & \text{if } N^{i*}(a, y; P, q^i) < 0 \\ \text{indeterminate} & \text{if } N^{i*}(a, yP, ; q^i) = 0 \\ +\infty & \text{if } N^{i*}(a, y; P, q^i) > 0. \end{cases}$$

Merchants:

Merchants give cash back to individuals and card companies for spending that is paid for by credit cards. To finance these transfers, each merchant adds a markup to its retail price. Suppose that each individual purchases all consumption from a single merchant. Then, conditional on a markup z, a merchant selling to an $\{i, P\}$ person with a credit card contract ω who is in state (a, y, m) receives the net transfer :

$$(z-1) \cdot c_v^i(a, y, m; P, \omega) - [\chi^i \cdot \psi^R + (1-\chi^i) \cdot \psi^{NR}] \cdot \min\{3 \cdot L(a, \omega),\ z \cdot \kappa \cdot c_v^i(a, y, m; P, \omega)\}$$

And selling to an $\{i, P\}$ person who is without a card and in state a, y, m, the merchant receives a transfer

$$(z-1) \cdot c_s^i(a, y, m; P), \quad s \in h, x, d.$$

Observe that since the markup z is common to all customers, the retailers are assumed to charge the same price to customers regardless of whether they are paying by a credit card (be it a reward card or a nonreward card) or cash.

We assume that there is a finite but large number of merchants, each of whom has a customer pool that mirrors the distribution of different types of individuals in the population and that all merchants charge a common markup. There is free entry into the merchant business. In equilibrium, the common markup will be such as to make aggregate net transfers zero.

3.2 Contact Probabilities and Market Tightness

We follow den Haan, Ramey, and Watson (2000) and assume that the matching function is

$$M\left(B^i\left(y,a;P,\omega\right),E^i\left(y,a;P,\omega\right)\right)=\frac{B^i\left(y,a;P,\omega\right)\cdot E^i\left(y,a;P,\omega\right)}{\left[B^i\left(y,a;P,\omega\right)^\zeta+E^i\left(y,a;P,\omega\right)^\zeta\right]^{1/\zeta}},\quad \zeta\geq 0\,,$$

where $B^i\left(a,y;P,\omega\right)$ denotes the mass of $\{i,P\}$ individuals in state (a,y) who are searching in the submarket ω and $E^i\left(a,y;P,\omega\right)$ denotes the mass of contact attempts made by the totality of card companies in the same submarket.

With this matching function, the probability that a credit card company will successfully contact a type i customer in state (a,y) is:

$$q^i\left(a,y;P,\omega\right)=\frac{M\left(B^i\left(\cdot\right),E^i\left(\cdot\right)\right)}{E^i\left(\cdot\right)}=\frac{1}{\left(1+\theta^i\left(a,y;P,\omega\right)^\zeta\right)^{1/\zeta}}=q(\theta^i(a,y;P,\omega)),\qquad(6)$$

where

$$\theta^i\left(a,y;P,\omega\right)=\frac{E^i\left(a,y;P,\omega\right)}{B^i\left(a,y;P,\omega\right)}.\qquad(7)$$

The ratio $\theta^i(a,y;P,\omega)$ is the tightness — from the perspective of card companies — of the submarket. A high value means stiff competition for customers and a low probability of a successful contact. On the other side, the probability that an $\{i,P\}$ individual in state (a,y) in the submarket ω will successfully contact a card company is

$$f^i\left(a,y;P,\omega\right)=\frac{M\left(B^i\left(\cdot\right),E^i\left(\cdot\right)\right)}{B^i\left(\cdot\right)}=\frac{\theta^i\left(a,y;P,\omega\right)}{\left(1+\theta^i\left(a,y;P,\omega\right)^\zeta\right)^{1/\zeta}}=f(\theta^i(a,y;P,\omega)).\qquad(8)$$

This probability is increasing in market tightness: A person can get a card quickly in a tight market.

3.3 Distributions

Given a contact probability function $f^i(a,y;P,\omega)$, the solution to the decision problem (1)-(5) implies an end-of-period distribution of type i people over the space (a,y,m,P,s,ω). Here a,y,m and P range over their respective domains, $s\in\{v,h,x,d\}$ ranges over the

various credit market states an individual could be in (with a contract, without a contract but eligible to get one, excluded from the credit market, and in default) and $\omega \in \{\Omega \cup \emptyset\}$ ranges over all feasible contracts and $\emptyset$, the latter for people without a contract. We denote these distributions by $G^i(a, y, m, P, s, \omega)$.

3.4 Equilibrium

An equilibrium is a market tightness function $\theta^{i*}(a, y; P, \omega) \geq 0$, a merchant markup z^*, and distributions $G^{i*}(a, y, m, P, s, \omega)$ such that

$$S^{i*}(a, y; P) = \max\left\{ \max_{\omega \in \Omega} \left\{ f(\theta^{i*}(a, y; P, \omega)) \cdot [V^{i*}(a, y; P, \omega) - H^{i*}(a, y; P)] + H^{i*}(a, y; P) \right\}, H^{i*}(a, y; P) \right\} \tag{9}$$

$$q^{i*}(a, y; P, \omega) = \begin{cases} 1 / \left[1 + f^{-1}\left(\frac{S^{i*}(a,y;P) - H^{i*}(a,y;P)}{V^{i*}(a,y;P,\omega) - H^{i*}(a,y;P)} \right) \right] & \text{if } V^{i*}(a, y; P, \omega) > H^{i*}(a, y; P) \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$q^{i*}(a, y; P, \omega) \Pi^{i*}(a, y; P, \omega) \leq P \cdot \tau \text{ for all } \omega \in \Omega \tag{11}$$

$$\left[q^{i*}(a, y; P, \omega) \Pi^{i*}(a, y; P, \omega) - P \cdot \tau \right] \theta^{i*}(a, y; P, \omega) = 0 \text{ for all } \omega \in \Omega \tag{12}$$

$$\begin{aligned} (z^* - 1) \sum_{i \in I} \mu^i \left[\int c_v^i(a, y, m; P, \omega) dG^{i*}(a, y, m, P, v, \omega) + \int c_s^i(a, y, m; P) dG^{i*}(a, y, m, P, s \neq v, \emptyset) \right] \\ - \sum_{i \in I} \mu^i [\chi^i \cdot \psi^R + (1 - \chi^i) \psi^{NR}] \times \\ \int \min\{3 \cdot L(a, \omega),\ z \cdot \kappa \cdot c_v^i(a, y, m; P, \omega)\} dG^{i*}(a, y, m, P, v, \omega) = 0 \end{aligned} \tag{13}$$

Equation (9) asserts that equilibrium values of S^i and θ^i must be consistent with individual optimization. The asterisks on S^i V^i, H^i and Π^i indicate that these functions implicitly

depend on $\theta^{i*}(a, y; P, \omega)$. The equilibrium contracts $\omega^{i*}(a, y; P)$ are the contracts that attain the inner max in (9).

Equation (10) is the equilibrium condition for directed search. The top branch asserts that for any contract ω offered to $\{i, P\}$ people in state (a, y) that delivers more utility than $H^{i*}(a, y; S^{i*})$, the market tightness must be such that the ex-ante value of searching for that contract is the same as the equilibrium ex-ante value of active search, $S^{i*}(a, y; P)$. The bottom branch asserts that any contract that delivers less utility than $H^{i*}(a, y)$ don't attract any customers and, so, $q^{i*}(a, y; P, \omega)$ is zero.

Equation (11) asserts that all feasible contracts earn nonpositive expected net profits.

Equation (12) is the complementary slackness condition that ensures consistency with free entry of lenders in any submarket: if equilibrium market tightness for a contract is strictly positive, the contract must earn zero expected net profits and if a contract generates negative expected net profits, its equilibrium market tightness must be 0. The conditions (11) and (12) together assert that contracts actually offered in equilibrium maximize expected net profits.

Equation (13) states that the surplus collected by merchants via markups exactly balances the transfers they send to individuals and card companies. The distributions G^{i*} are the distributions implied by the optimal decision rules of individuals and card companies, given $\theta^{i*}(a, y; P, \omega)$.

The aggregate measures searchers in different markets, $B^{i*}(a, y; P, \omega)$, and the aggregate measure of posted contracts in that market, $E^{i*}(a, y; P, \omega)$, do not appear directly in these equilibrium equations because these quantities effect equilibrium outcomes only through $\theta^{i*}(a, y; P, \omega)$. They can be backed out from knowledge of equilibrium market tightness function and the equilibrium contract in each market.[13] The aggregate measure of posts in this (sub)market is then $E^{i*}(a, y; P, \omega^*) = B^{i*}(a, y; P, \omega^*) \cdot \theta^{i*}(a, y; P, \omega^*)$.

3.5 Scaling With Respect to the Permanent Component P

Given the assumptions of our model, the equilibrium decision rules, value functions, market tightness functions, and contracts vary with P in a determinate fashion. To state these scaling properties, define the scaled contract for an $\{i, P\}$ person in state (a, y) as the contract $\{R^*(a/P, y; 1),\ P \cdot \underline{a}^{i*}(a/P, y; 1)\}$, i.e., as the equilibrium contract offered to an $\{i, P = 1\}$

[13] For instance, if in steady state individuals of type $\{i, P\}$ with persistent income y and savings a search for contract ω^*, then $B^{i*}(a, y; P, \omega^*)$ is just μ times the steady state measure of $\{i, P\}$ people who do not possess a card, are not excluded from the credit market and are in state $\{a, y\}$. These include households that separated from their cards at the start of the current period and those who entered the period without a card.

person with asset a/P and persistent income component y, except that the credit limit is scaled by P.[14] Let $\Omega_P^{i*} = \cup_{a,y}\{R^{i*}(a/P, y; 1),\ P \cdot \underline{a}^{i*}(a/P, y; 1)\}$ be the set of all such scaled contracts for $\{i, P\}$ individuals. For any $\omega_P^{i*} \in \Omega_P^{i*}$, let ω_1^{i*} be the corresponding $P = 1$ contract, i.e, the contract $\{R^{i*}(a/P, y; 1),\ \underline{a}^{i*}(a/P, y; 1)\}$.

Proposition 1. If $\{R^{i*}(a, y; 1),\ \underline{a}^{i*}(a, y; 1)\}$ is the equilibrium contract offered to an $\{i, P = 1\}$ person in state (a, y), there is an equilibrium in which an $\{i,\ P\}$ person is offered the scaled contract $\{R^{i*}(a/P, y; 1),\ P \cdot \underline{a}^{i*}(a/P, y; 1)\}$ and in which the following scaling properties hold:

- $c^{i*}(a, y, m; P, \omega_P^{i*}) = P \cdot c^{i*}(a/P, y, m; 1, \omega_1^{i*})$, $a'^{i*}(a, y, m; P, \omega_P^{i*}) = P \cdot a'^{i*}(a/P, y, m; 1, \omega_1^{i*})$, and $d^{i*}(a, y, m; P, \omega_P^{i*}) = d^{i*}(a/P, y, m; 1, \omega_1^{i*})$
- $S^{i*}(a, y; P) = P^{1-\gamma} S^{i*}(a/P, y; 1)$, $h^{i*}(a, y, m; P) = P^{1-\gamma} \cdot h^{i*}(a/P, y, m; 1)$, $x^{i*}(a, y, m; P) = P^{1-\gamma} \cdot x^{i*}(a/P, y, m; 1)$, $v_{\text{DEF}}^{i*}(y, m; P) = P^{1-\gamma} \cdot v_{\text{DEF}}^{i*}(y, m; 1)$, $v^{i*}(a, y, m; P, \omega_P^{i*}) = P^{1-\gamma} \cdot v^{i*}(a/P, y, m; 1, \omega_1^{i*})$, and $\xi^{i*}(a, y; P) = \xi^{i*}(a/P, y; 1)$
- $\theta^{i*}(a, y, P; \omega_P^{i*}) = \theta^{i*}(a/P, y; 1, \omega_1^{i*})$
- $\pi^{i*}(a, y, m, P; \omega_P^{i*}) = P \cdot \pi^{i*}(a/P, y, m; 1, \omega_1^{i*})$

Proof. Since contract posting costs scale with P, the existence of such an equilibrium follows directly from the homogeneity of degree $1-\gamma$ of the period utility function and the fact that P enters the budget set as a factor multiplying $y + m$. □

3.6 Computation

Given Proposition 1, we need only solve for the equilibrium of the model for $P = 1$ since the equilibrium quantities for other P's are just scaled version of the $P = 1$ equilibrium.

For our quantitative analysis, we compute an approximate equilibrium of our model. First, the space of assets a is approximated by a fine grid. Next, for each $\{i, y\}$ pair, contracts for K asset levels $\{0, a_2^i, a_3^i, \ldots, a_K^i\}$ only are offered. An $\{i, a, y\}$ is offered the contract for person $\{i, a_k^i, y\}$, where a_k^i is the closest asset level less or equal to a. For a given $\{i, a_k^i, y\}$, $\underline{a}$ and R are treated as continuous variables and first order conditions are used to pin them down.

[14] If person A has twice the assets and twice the P as the P=1 person, then A's scaled contract has the same interest rate but twice the credit limit as $P = 1$'s contract.

Table 1
Income Process Parameters

Parameter	Description	Value
ρ	Autocorrelation of log of persistent component	0.938
σ_ε	Std. of innovation to log of persistent component	0.138
σ_z	Std of log transitory shock	0.257
σ_α	Std of permanent shock	0.29

Notes: Source: Storesletten, Telmer, and Yaron (2004, p. 705, Table 2, Row E). All parameters are at annual frequency. The value of 0.29 for σ_α is below the 0.301 value reported in their table. A smaller value was chosen to maintain a close match between the distribution of the incomes implied by the process and the distribution of incomes reported in our data.

4 Mapping the Model to the Data

4.1 Income Process

We calibrate the earnings process based on estimates provided in Storesletten, Telmer, and Yaron (2004). These authors estimate an earnings process for annual earnings given by $y(t)z(t)\alpha^i$, where y, the persistent component of earnings, is an AR1 process in logs, z, the transitory component, is i.i.d. with $\ln(z)$ having standard deviation σ_z, and α^i is permanent individual component with $\ln(\alpha)$ having standard deviation σ_α. Their estimates are reported in Table 1.

Our model period is a quarter and we assume that income is the sum of the persistent and transitory components: $y + m$. We assume that $\ln(y_t) = \rho \ln(y_{t-1}) + \varepsilon_t$ and that m is uniformly distributed with support $[-\lambda y, \lambda y]$, given y. Note that this latter assumption is equivalent to assuming that z is uniformly distributed with support $[(1-\lambda), (1+\lambda)]$. We discretize y into 5 levels and assume that it follows a first-order Markov process. We pick λ and the values of the Markov transition matrix such that the model earnings generate a ρ, σ_ε and σ_z at annual frequencies that matches what is reported in Table 1.

4.2 Parameters Set Independently

Table 2 displays the other parameters whose values are set independently. The (real) risk-free (gross) rate R_f was set at 1.02 percent annualized and the probability of survival, ν, at 0.82 percent annualized. The CRRA parameter γ was set at 2, which is conventional in macroeconomics.

Table 2
Parameters Set Independently

Parameter	Description	Value
λ	Bounds for transitory shock	0.826
R_f	Gross risk-free rate	1.005
ν	Probability of survival	0.998
γ	Curvature of CRRA utility function	2.0
δ	Entry rate after default	1/28
τ	Cost of posting a contract	0.001
η	Probability of searching for a card	0.50
ξ	Probability of exogenously separating from card	0.022
ζ	Elasticity of the matching function	1.00
ψ^R	Cashback rate for reward cards	0.06
κ	Share of spending that can be paid by card	0.58
–	Share of reward types in the population	0.67

Notes: All rates and probabilities are at quarterly frequency.

The cost of posting a contract, τ, is set to 0.001, a value low enough to ensure that a profitable credit card exists for all $\{i, a, y\}$ triples. The probability of search following a separation, η, is set at 0.50: Delays in getting a new card creates a lock-in effect for existing cards which increases profits.

The entry probability following default, δ, is set so that the average period of exclusion from the credit card market following default is 7 years.

The separation parameter, ξ was set to 0.022. We pin this down from the observed frequency, between June 2014 and May 2019, of accounts in good standing that disappear from our sample.

The elasticity of the matching function ζ is set to 1.

The estimates reported in https://www.consumerfinance.gov/data-research/research-reports/the-consumer-credit-card-market suggest a monthly reward of 1.8 percent. But this estimate excludes non-pecuniary rewards like concierge service, lounge access, free bag checking for flights, or travel insurance. We set ψ^R set to 0.02.

We assume that 67 percent of the population are reward types, which is the average share of reward cards (by scores or by incomes) shown in Figure 1.

4.3 Estimation

The number of types I and the fraction of each type μ^i is prespecified. With these given, the estimation locates the $\{\beta^i, \phi^i\}$, $i \in \{1, 2, \ldots, I\}$ pairs and ψ^{NR} that minimize the objective function:

$$
\begin{aligned}
&w_1 \sum_{j=1}^{5} f_j^{\text{model-rew}} \left(\text{CL-to-INC-rew}_{\text{score}_j}^{\text{model}} - \text{CL-to-INC-rew}_{\text{score}_j}\right)^2 + \\
&w_1 \sum_{j=1}^{5} f_j^{\text{model-norew}} \left(\text{CL-to-INC-norew}_{\text{score}_j}^{\text{model}} - \text{CL-to-INC-norew}_{\text{score}_j}\right)^2 + \\
&w_2 \sum_{j=1}^{5} f_j^{\text{model-rew}} \left(\text{DEF-FRQ-rew}_{\text{score}_j}^{\text{model}} - \text{DEF-FRQ-rew}_{\text{score}_j}\right)^2 + \\
&w_2 \sum_{j=1}^{5} f_j^{\text{model-norew}} \left(\text{DEF-FRQ-norew}_{\text{score}_j}^{\text{model}} - \text{DEF-FRQ-norew}_{\text{score}_j}\right)^2 + \\
&w_3 \sum_{j=1}^{5} \left([\text{APR-rew}_{\text{score}_j}^{\text{model}} - \text{APR-norew}_{\text{score}_j}^{\text{model}}] - [\text{APR-rew}_{\text{score}_j} - \text{APR-norew}_{\text{score}_j}]\right)^2
\end{aligned}
$$

Here, $\text{CL-to-INC-rew}_{\text{score}_j}$, $\text{DEF-FRQ-rew}_{\text{score}_j}$, and $\text{APR-rew}_{\text{score}_j}$ are the average credit-limit-to-income ratio, default frequency, and APR in the jth score quintile for reward cards and the $\text{-norew}_{\text{score}_j}$ terms are analogous quantities for nonreward cards.

The purely reward statistics are weighed by the model share, $f_j^{\text{model-rew}}$, of reward people in a given bin (and similarly for nonreward statistics). The estimation gives the most weight to the default frequency deviations ($w_2 = 500$), some weight to the Δ APR deviations ($w_3 = 25$), and the least weight to credit-limit-income-ratio deviations ($w_1 = 1$).

The settings of μ^i importantly affect the composition of model bins with respect to scores and incomes. We postulate 3 groups of people with regard to (β, ϕ) pairs. The most impatient group (the group with smallest β) is assumed to comprise 25 percent of the population, and the other two groups comprise 37.5 percent each. The most impatient group is assumed to be a smaller portion of the population because of the sharp change in the default behavior between the lowest credit score bin and the next one for reward and nonreward types and having more types closer to that region improves the performance of the model. Within each group a fraction 0.67 are assumed to be reward types and the rest are nonreward types.

Table 3
Parameter Estimates

Type i	Discount factor β^i	Default Cost ϕ^i	Cashback on Nonreward Cards ψ^{NR}
1&4	0.59	0.20	
2&5	0.87	0.23	
3&6	0.94	0.63	
All			0.0006

Notes:

These settings imply that there are 6 types of people in the economy. Using $i = 1, 2, 3$ to denote reward types and $i = 4, 5, 6$ to denote nonreward types, the values of $\mu^i, i = 1, 2, \ldots, 6$ as follows: $\mu^1 = 0.25 \times 0.67$; $\mu^2 = 0.375 \times 0.67$; $\mu^3 = 0.375 \times 0.67$; $\mu^4 = 0.25 \times 0.33$; $\mu^5 = 0.375 \times 0.33$; $\mu^6 = 0.375 \times 0.33$. Thus $i = 1$ is the most impatient reward type, $i = 4$ is the most impatient nonreward type and so on.

The estimated parameters are given in Table 3. People are estimated to be quite impatient. The most impatient type (Types 1 and 4) discount the future at a 70 percent quarterly rate, while the least impatient type (Types 3 and 6) discount at a 6 percent quarterly rate. The costs of default are estimated to be positively related to patience: The most impatient types forfeit 20 percent of their transitory income to creditors upon default, whereas the least impatient type forfeit 63 percent. The value of the cashback to card companies on nonreward cards is estimated to be 6 basis points. This estimate is very low compared to the merchant fees card companies charge on nonreward cards. Some of the reasons for the low estimate is discussed later.

The model-implied distribution of types across the score bins is displayed in Table 4. Note that the most impatient types populate the bottom two bins of the score distribution while the most patient type mostly populate the top two bins. The middle impatience type (Types 2 and 5) mostly populate the middle three bins.

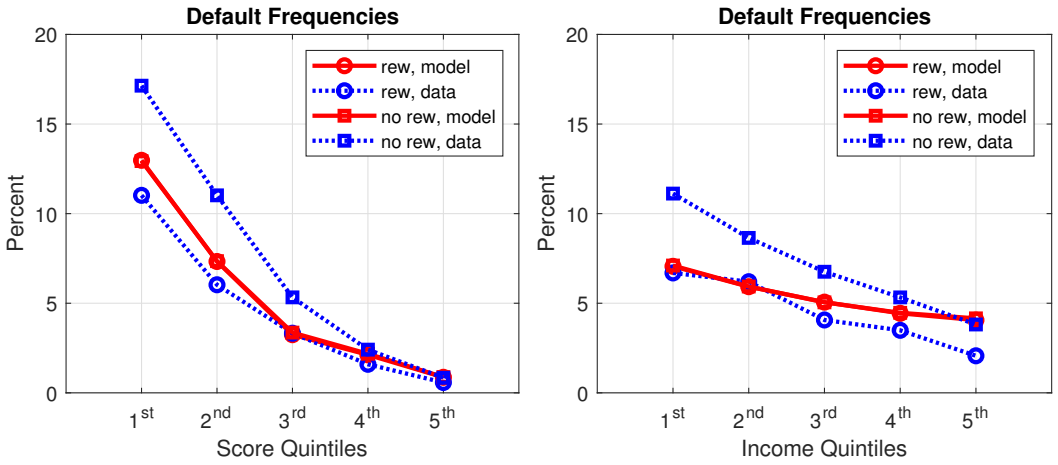
Figure 5 displays default frequencies with respect to credit scores (left panel) and incomes (right panel). The data moments in the left panel are targeted by the estimation. In the data, conditional on the credit score, the default rate on nonreward cards is lower than the default rate on reward cards. This is especially pronounced for the lowest credit score bin. We create the possibility of such an outcome by assuming that credit scores are computed without knowledge of an individual's reward type. With this assumption, the model can qualitatively match the fact that default frequencies conditional on credit scores are lower

Table 4
Type Distribution of New Originations

Type	Score Quintiles					Frac.
i	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	
1&4	0.70	0.30	0.00	0.00	0.00	0.29
2&5	0.00	0.26	0.40	0.23	0.10	0.44
3&6	0.00	0.00	0.08	0.36	0.56	0.27

Notes: Model outcomes.

Figure 5

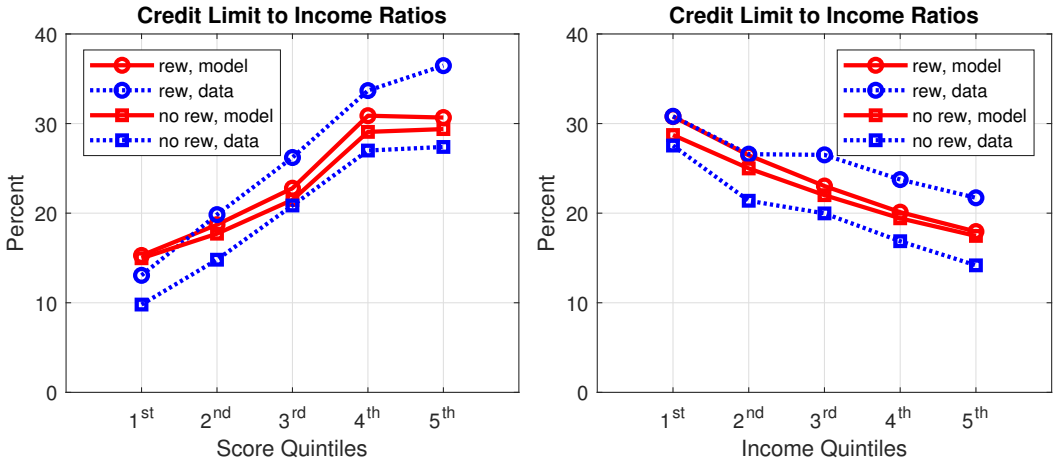


for reward types than for nonreward types. However, the magnitude of the gap is very small relative to the data and is not discernible in the figure.

The right panel depicts the default frequency by income bins. In the model, the default rate on the reward cards is lower conditional on credit scores, but by a small amount. This is qualitatively in line with the data, but it quantitatively does not match the large difference in default rate seen in the bottom credit score bin. In the model, the optimal contract is such that the bank increases the credit limit on reward cards but keeps the expected default rate roughly constant at the new credit limit.

Figure 6 turns to credit-limit-to-income ratios, where the left panel moments are targeted. As in the data, the model predicts higher credit limits for reward cards relative to nonreward cards, but the magnitude of the gap is smaller than in the data. In the model, rewards act like higher default costs: If the person defaults, the individual cannot get the 2 percent reward on consumption expenditures done using the reward credit card while it is excluded from financial markets. On the other hand, there is a difference in how much individuals use the credit card for transactions. The impatient type is less able to use the card for transactions, given that a larger portion of the credit line is taken up in revolving balances

Figure 6



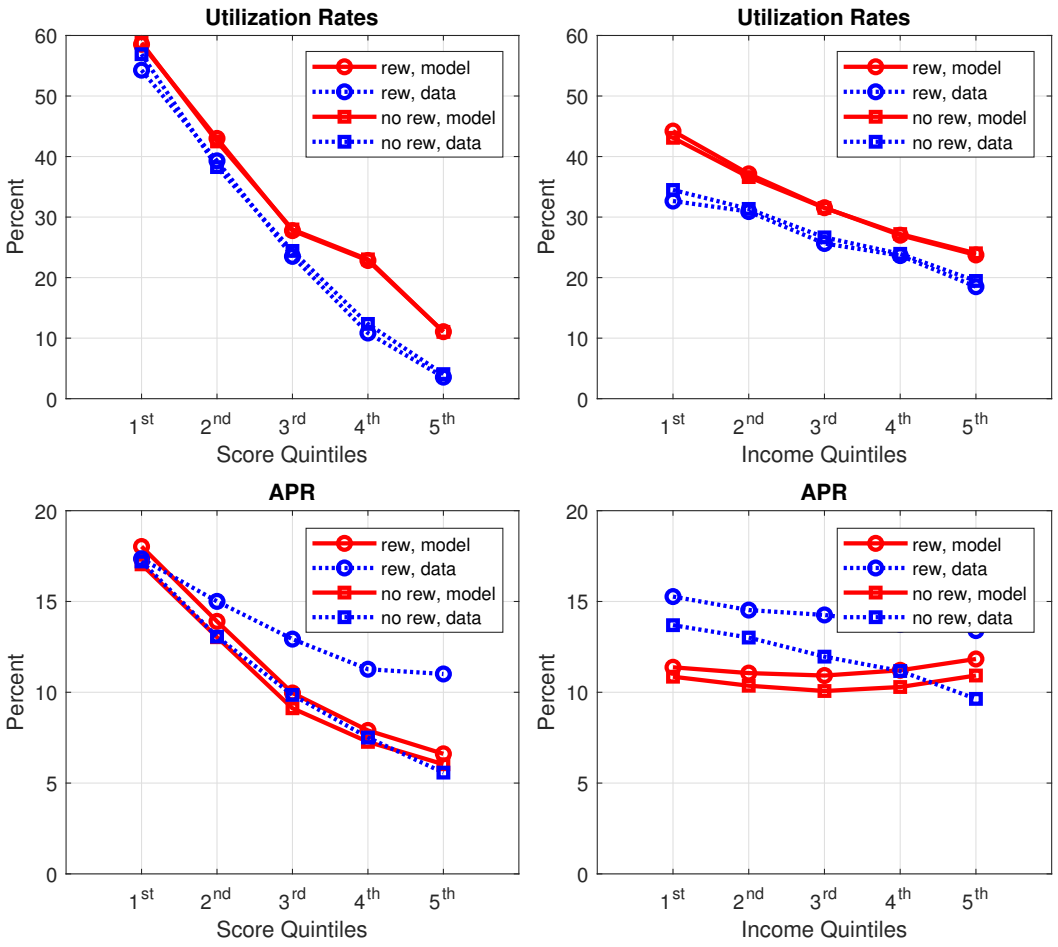
and so less is available for new transactions. If a card is used less for transactions, and so less rewards are earned on it, the increase in default cost will also be smaller. Given that most of the rewards are earned in the future, discounting also plays a role, and types that discount the future at a very high rate are less averse to losing future rewards. Finally, if credit is limited (due to low default costs), the percentage increase in credit limit of reward cards might be higher.

The top panel of Figure 7 shows that the utilization rate for both reward and nonreward cards. These moments are not targeted. The model utilization rates are somewhat higher than in the data but the model captures the fact that the utilization rates across reward and nonreward cards are very similar.

The bottom panel shows the outcome with respect to interest rates. As in the data, the interest on reward cards is higher than reward cards. One reason for this is the cashback to card companies on transactions made with nonreward cards, namely, ψ^{NR}. This pure revenue flow leads, in competition, to lower interest rate and higher credit limits on nonreward accounts. The higher is ψ^{NR} the bigger the difference between interest rates between reward and nonreward card and smaller the difference in credit limits between reward and nonreward cards. The estimate of ψ^{NR} balances these two effects. Because the effect of ψ^{NR} is very powerful in the model, a small value is sufficient to create a gap in APRs between reward and nonreward cards.

In reality, the interchange fee collected on nonreward cards is well above 1 percent, so the estimated value of ψ_{NR} is counterfactually low. There are a couple of reasons for this. First, while our estimate of ψ_{NR} seeks to match the difference in APR between reward and nonreward cards, it underpredicts both the APR and default frequency on nonreward cards.

Figure 7


Utilization Rates
Percent
Score Quintiles
Income Quintiles
APR
rew, model
rew, data
no rew, model
no rew, data
1st
2nd
3rd
4th
5th
0
10
20
30
40
50
60
5
15

These misses suggest more subsidies are going to nonreward cards than we have estimated. Another reason for the low value of ψ_{NR} is that people may not be using their nonreward cards for transactions as much as we assume they do in the model. A discrepancy here will depress the value of ψ_{NR}.

5 Credit Effects of Rewards and Retained Interchange Fees

In this section, we present a simplified version of our model to illustrate how rewards and retained interchange fees can influence the terms of credit.

There are two periods, denoted $t = 0, 1$. Income is a constant Y in both periods. Individuals have no inherited debt, i.e., $B = 0$. If the individual borrows in period 0, her cost of default in period 1 is $\chi > 0$.

In period 0, the individual is offered a credit line with an interest rate R and a limit L. We assume that lenders never offer contracts that feature contractually feasible debt levels on which default is certain (this is a perfection requirement). Therefore, all offered contracts must satisfy $R \cdot L \leq \chi$. Given this, competition among lenders will ensure that all contracts will offer the risk-free rate R_f.[15] We also assume that given R_f, lenders offer the maximum credit limit they can, namely, $L = R_f/\chi$.

The optimal B' solves

$$\begin{cases} u'(y + B') = \beta \cdot R_f \cdot u'(y - R_f \cdot B') & \text{if } u'(y + \frac{\chi}{R_f}) < \beta \cdot R_f \cdot u'(y - \chi) \\ B' = L & \text{otherwise.} \end{cases}$$

We will assume that β and/or χ are low enough, so that the inequality in the first branch is violated and the optimal choice is to borrow to the limit. Then, $c_0 = y + L$ and $c_1 = y - R_f \cdot L$.

Now suppose that the credit card company has some funds $z > 0$ to disburse. Later on, we will connect z to interchange fees; for now, think of it as some revenue the card company wishes to disburse to the cardholder as an inducement. There are two ways to do this: give it as cashback, which will increase the cardholder's current income, or use it to subsidize borrowing, which will increase her credit limit.

The cashback option will increase the period 0 income to $y + z$. Assuming that the consumer is still constrained by the credit limit, c_0 rises to $y + L + z$ and c_1 remains unchanged at $y - R_f \cdot L$.

[15] If an individual accepts a contract with $R > R_f$ and borrows some amount B', a competitor could offer a contract with a slightly lower R that the individual would strictly prefer and on which the competing lender can make profits.

The other option is to use the revenue to lower interest rates on the card. Call the subsidized rate $R' < R_f$. Importantly, the subsidy will also raise the borrowing limit since the limit L' will solve $L' = \chi/R'$. If we continue to assume that the individual borrows to the limit, we can determine how much R' can be lowered below R_f to use up the funds z. Specifically, R' will solve

$$R'L' + z \cdot R_f = R_f \cdot L'. \tag{14}$$

The first term on the l.h.s. is what the card company earns in interest from the cardholder. Since z is now retained revenue, the second term is the interest earned on it. The r.h.s. represents the costs of lending L'.

Which strategy is better for the cardholder? Under the first strategy, the cardholder's consumption in period 0 goes up by z and c_1 stays unchanged at $y - R_f \cdot L = y - \chi$. In the second strategy, consumption in period 0 goes up by the amount $L' - L$. To connect this to z, note that we can substitute $R_f L$ for $R'L'$ on the l.h.s. of (14), since both products equal χ. Doing so yields:

$$R_f L + z \cdot R_f = R_f \cdot L' \quad \Rightarrow \quad L' - L = z.$$

And, consumption in period 1 is $c_1 = y - R'L' = y - \phi$. Thus, for a constrained cardholder, the cashback strategy is equivalent to the borrowing-subsidy strategy.

But this equivalence breaks once we recognize that z is generated by an interchange fee levied on merchants. For the constrained cardholder, the interchange fee paid by merchants to the card company is a fraction Ψ of the amount borrowed in period 0. Since period-0 borrowing is L under the cashback strategy and $L' > L$ under the borrowing-subsidy strategy, the revenue collected is larger under the latter. Since the revenue is paid back to the cardholder in either case, the cardholder should prefer the borrowing-subsidy strategy over the cashback strategy. We can demonstrate this formally by setting z, the fee collected under the cashback regime, to $\Psi \cdot L$ and by setting z', the fee collected under the borrowing-subsidy regime, to $\Psi \cdot L'$. Then, period 0 consumption for the cashback regime is

$$c_0 = y + \Psi \cdot L + L = y + [1 + \Psi] \cdot \frac{\chi}{R_f},$$

and for the borrowing-subsidy strategy is

$$\begin{aligned} c_0' &= y + L' \\ &= y + L' - L + L \\ &= y + z' + L \\ &= y + \Psi L' + L \\ &= y + \left[1 + \Psi \frac{L'}{L}\right] \cdot \frac{\chi}{R_f} \end{aligned}$$

Since $L'/L > 1$, the cardholder gets to consume more in period 0 under the borrowing-subsidy strategy. In competition, lenders will gravitate to passing on the interchange fee in the form of a borrowing subsidy.

Next, consider the case where the cardholder is not constrained by the credit limit in period 0. In this case, we will find the opposite result: the cashback strategy is better than the borrowing-subsidy strategy for the cardholder.

6 Measuring the Credit Effects of Rewards and Interchange Fee Revenue

In this section, we use the quantified model to measure how cashback programs affect contract terms and welfare for different types of contracts.

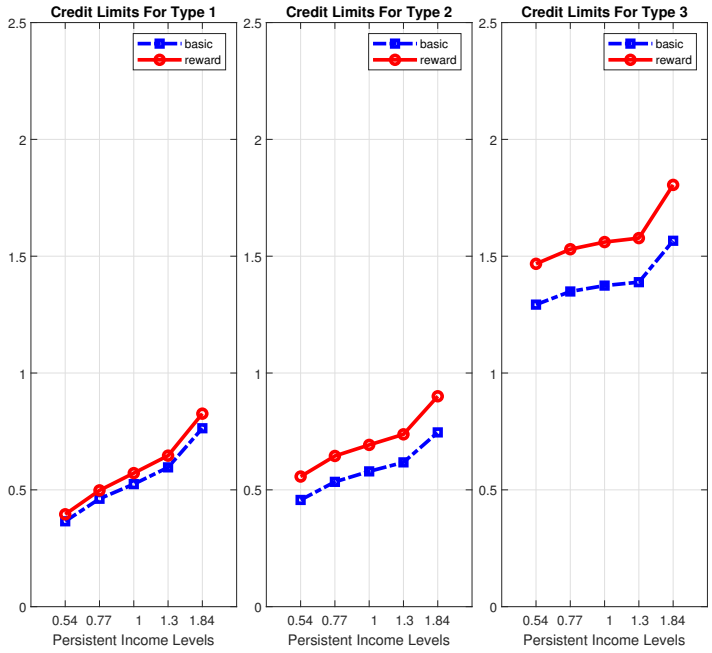
6.1 Rewards Cards

We focus on how rewards change the credit limits and interest rates on zero-asset contracts, i.e., contracts offered to individuals with little or no assets. The effects are qualitatively similar for contracts offered to people with positive assets.

To measure these effects, we do the following experiment: We make a negligible measure of reward and nonreward types ineligible for reward and nonreward cards. Instead, they are eligible only for a card that does not give any rewards to cardholders or give any cashback to banks. We label the equilibrium contract offered to these people as the "basic" contract. Since the measure of these new types of cardholders is negligible, their presence does not affect the retail markup. By comparing the credit limits and interest rates on the basic card to the terms offered on the corresponding reward and nonreward cards, we can assess how rewards and cashback to banks affect credit terms.

Figure 8 compares the credit limits on basic cards to those on reward cards. From left to right, the panels display the credit limits for the most to the least impatient types. Rewards

Figure 8



raise credit limits quite substantially for middle and least impatient types. In percentage terms, credit limits on reward cards for the middle type increases between 30 and 35 percent and between 12 and 15 percent for the least impatient type. The leftmost panel shows that credit limit effects of rewards is smaller for the most impatient type, with the percentage increase in limits ranging between 8 and 10 percent.

Rewards also lower contract interest rates, as shown in Figure 9. For the most and least impatient types, the decline in interest rate ranges between 7 and 8 percent, generally. For the middle type, the decline is larger, ranging between 21 and 24 percent.

What explains these effects? As mentioned earlier, rewards act like an increase in default costs: During the period of exclusion following a default, the person cannot get any rewards on purchases. Higher default costs lower the probability of default and, in response, card companies offer higher credit limits and lower interest rates.

The size of these effects are weakest for the most impatient type (Type 1). The reason is that the most impatient type use their cards to revolve debt more than the other two types, and, so, their capacity to put purchases on their cards is lower. This is shown in Figure 10 which plots the average share of purchases made with credit cards across persistent income levels for different types. Second, the most impatient type places less value on the rewards lost in the exclusion periods following a default as this loss happens in the future. Therefore, reward are less effective in blunting default incentives.

Figure 9

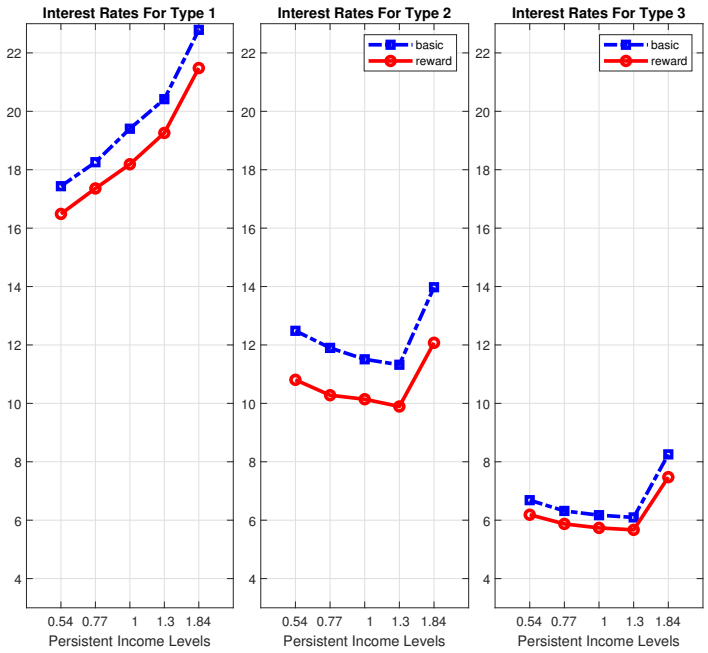
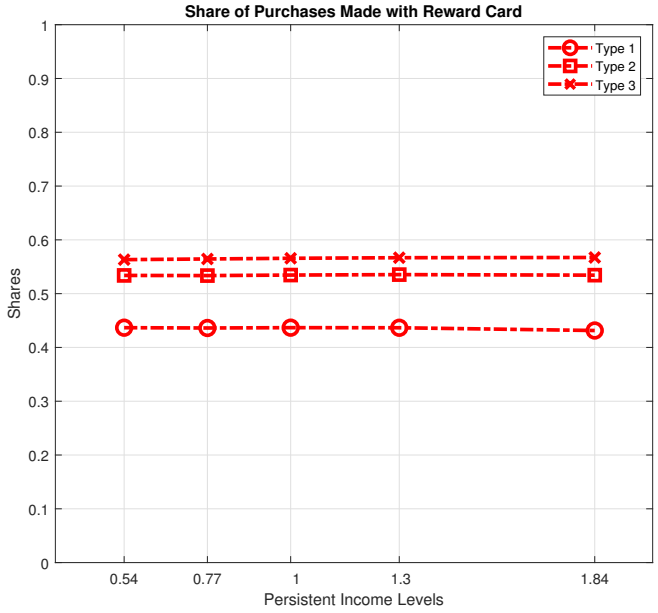


Figure 10



6.2 Nonreward Cards

For nonreward cards, the card company gets cashback on purchases made on the card. Although the cash back is a very modest 6 basis points, it nevertheless raises credit limits and lowers interest rates significantly, as shown in Figures 11 and 12. In percentage terms, the increase in credit limit ranges between 1 and 6 percent for the most impatient and the least impatient types, and between 13 and 21 percent for the middle types. The decline in interest rate ranges between 3 and 9 percent for the least and most impatient types, and between 21 and 53 percent for the middle type.

These effects arise because the cashback creates a pure revenue flow, which raises profits on nonreward cards. Competition among card companies leads to these profits being dissipated via higher limits and lower interest rates on the cards. Notice that higher limits work to raise the payment capacity of a card and, therefore, tends to increase the revenue earned from cashbacks. The lowering of interest rates, however, does eat into profits. Absent the cashback, the increase in limits and reduction in interest rates would lead to losses for the card companies. However, the cashbacks balance these losses. In effect, the cashback to card companies act as subsidy for nonreward cards.

Figure 11

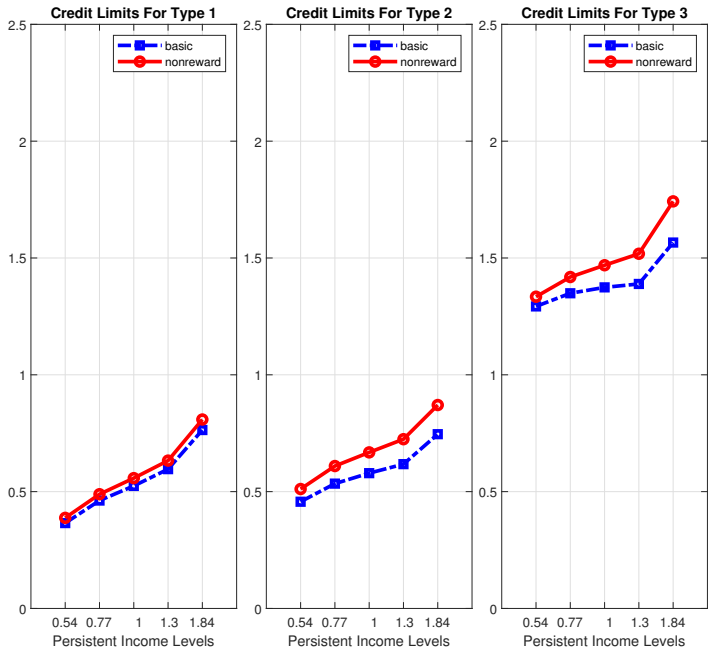
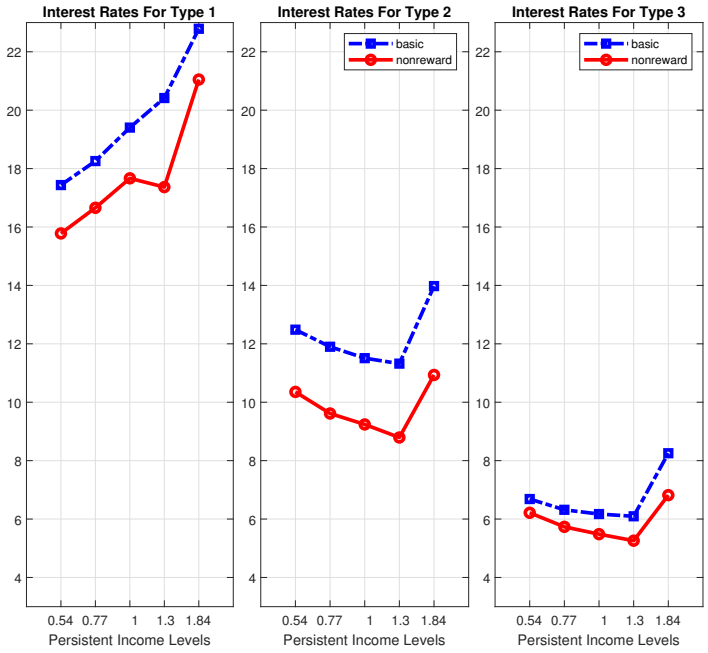


Figure 12



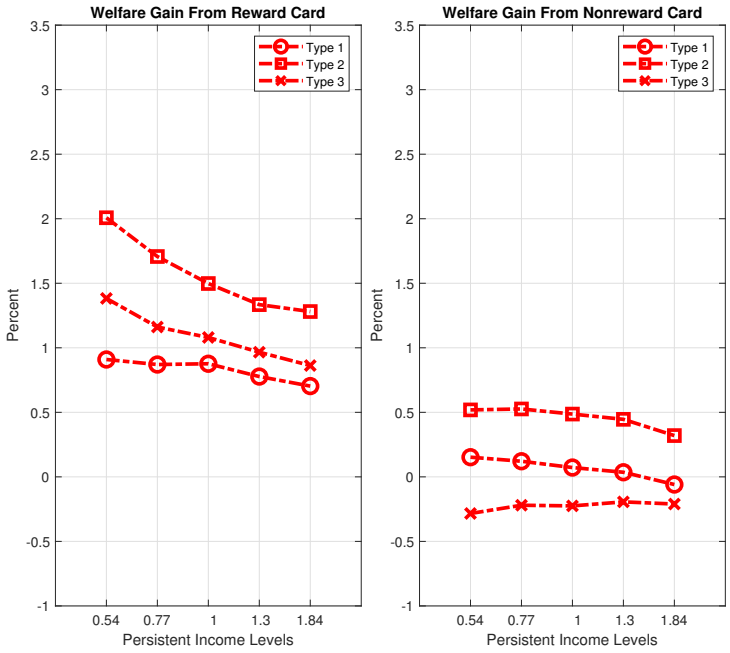
6.3 Welfare Effects of Reward and Nonreward Cards

We have shown that rewards and cashbacks to card companies raise credit limits and lower contract interest rates. Thus the small measure of individuals who were made ineligible for reward and nonreward cards were clearly made worse off. This fact raises the question of whether cashback programs are welfare improving for those who receive reward and nonreward cards, taking into account that merchants finance these programs by raising the prices of products sold.

The left panel of Figure 13 reports the welfare gain, in terms of consumption equivalents, for people searching for a reward card, having zero assets. The right panel shows the same information for people searching for nonreward card. The reported gains take into account that moving from an economy with only basic cards to the baseline model leads to a 0.63 percent increase in price. Thus, even taking into account the increase in prices, all reward and nonreward types are better off in the baseline economy, relative to the basic card economy.

The figure also shows that cashback programs have strong distributive effects. For instance, within the group of reward cardholders, the welfare gain is higher for lower levels of $\mathtt{y}$. This makes senses, since individuals with lower $\mathtt{y}$ are more liable to borrow and, so, benefit from the higher credit limits and lower interest rates. This pattern is also generally true for the group of nonreward types.

Figure 13



7 Lowering Fees and Banning Rewards: A Policy Experiment

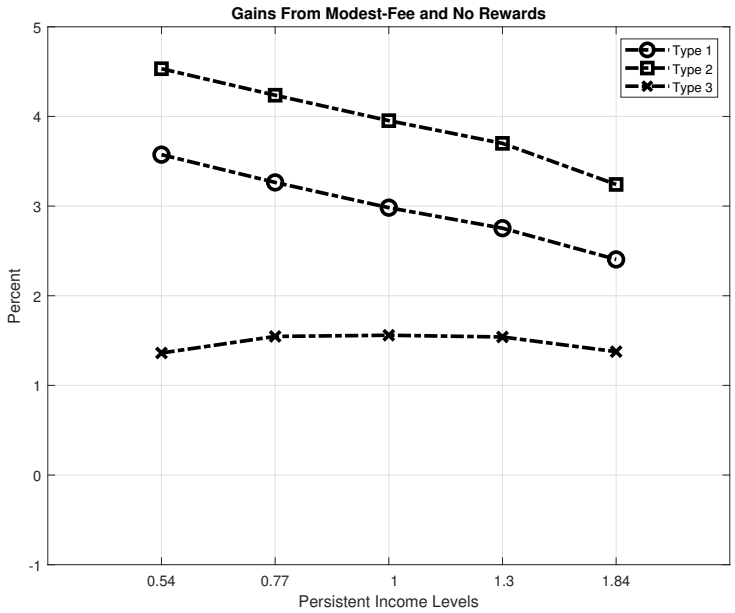
In the previous section we showed that fees on nonreward cards powerfully subsidize credit card lending. Motivated by this finding, and the fact that interchange fees outside of North America are typically quite modest[16] we do the following experiment. We compute the equilibrium of an economy in which the fee on credit card transactions are set at a low value of 0.5 percent and rewards are prohibited. In other words, all cards are nonreward cards and the fee acts as a subsidy to credit cards (financed by a markup on prices). We compute the welfare gains from moving from the basic card economy (no fees or rewards) to this modest-fee-no-rewards economy. We compare these welfare gains with the welfare gains from moving from the basic card economy to the baseline economy and draw some conclusions.

Figure 14 displays the welfare gains from moving from the basic card economy to the modest-fee-no-rewards economy. To be clear, these gains represent the percentage by which consumption in the basic card economy must be scaled up to equate the lifetime utilities of newly-born zero assets individuals who are searching for a credit card in basic card economy to the lifetime utility of the same individual in the modest-fee-no-rewards economy. The figure shows that the consumption equivalents are quite substantial: For the least impatient

[16] According to industry sources (https://marketing.cmspi.com/view/49137163/) interchange fees are less than 0.5 percent in EU countries, U.K., and China and less than 1 percent in New Zealand and Australia. The U.S., Canada and Mexico have fees in excess of 1.5 percent, with the interchange fee being the highest in the U.S.

type, the gain ranges between 4 percent and slightly above 6 percent. For the middle and most impatient types, the gains are comparable and range between little under 3 percent to little under 5 percent.

Figure 14



A comparison to Figure 13 reveals the welfare gains from moving to the modest-fee-no-rewards economy dominates the welfare gains experienced by reward and nonreward types from moving from the basic card economy to the baseline economy. One reason for this is that the increase in prices in the modest-fee-no-rewards economy is only 0.23 percent as opposed to 0.63 percent in the baseline economy. Aside from this, the main reason for the large gains is the expansion in the credit limit and reduction in interest rates on credit cards that is brought about by the subsidy. Since this expansion of the budget set is most valuable to people with low y, the welfare gains is declining in the value of the persistent income state.

Why does subsidizing credit cards have such a large positive effect on welfare? By permitting card companies to keep 0.5 percent of all purchases made on a card, the policy effectively commits a portion of cardholders' future incomes to the card companies. Since individuals cannot voluntarily make such commitments, the welfare gains shown in Figure 14 cannot be obtained through purely private means. Thus, the fact that there is any welfare gain at all stems, fundamentally, from individuals inability to commit. The fact that the gains are so large is the result of the low estimated discount factors. Impatient people would like to borrow and this policy change enables that.

If subsidizing credit is much better than giving out rewards, why do credit card companies offer rewards? We think the reason might be due to the fact that individuals can hold more than one credit card, which our model did not allow due to tractability problems. In a world where individuals can get more than one credit card, if one card gives no rewards and charges low interest rates, and another one gives high rewards and charges high interest rates, the individual would use the low interest rate card for borrowing, and use the high reward one for transactions. This would shut down the possibility of using the interchange fees to subsidize low interest rates. Our policy experiment suggests that in a competitive enough credit card market, disallowing rewards and so shutting down competition on rewards might increase welfare.

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