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A Quantitative Theory of Information and Unsecured Credit*

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Abstract

Over the past three decades five striking features of aggregates in the unsecured credit market have been documented: (1) rising availability of credit along both the intensive and extensive margins, (2) rising debt accumulation, (3) rising bankruptcy rates and discharge in bankruptcy, (4) rising dispersion in interest rates across households, and (5) the emergence of a discount for borrowers with good credit ratings. We show that all five outcomes are quantitatively consistent with improvements in the ability of lenders to observe borrower characteristics. Part of our contribution is the development of an algorithm for computing equilibria with asymmetric information and individualized pricing. From a welfare perspective, our main finding is that more information is better *ex ante*, even though better information can rule out pooling outcomes that some groups might find beneficial *ex post*.

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1 Introduction

For most of the postwar period the unsecured market for credit has been small. Ellis (1998) shows that truly unsecured credit (credit card and related plans issued by insured banks) did not appear in any significant amount until the late 1960s. Furthermore, as Figure (1) shows, the filing rate for Chapter 7 bankruptcy over the past 70 years was flat and very low until the late 1970s, reflecting the absence of significant unsecured indebtedness.[1]

However, over the past three decades there have been dramatic changes in this market. First, the availability of unsecured credit has increased both along the extensive and intensive margin; Narajabad (2007) documents that the fraction of U.S. households with positive credit card limits increased by 17 percentage points between 1989 and 2004, while the average credit limit more than doubled over the same time period. In addition to the increase in availability of credit, Krueger and Perri (2006) measure that unsecured debt (utilized credit) as a fraction of disposable income has risen from 2 percent to 9 percent from 1980 to 2005. Given the presence of exemptions, the best measure of unsecured credit is negative net worth; Sánchez (2008) documents that the mean debt to mean income ratio has risen from 0.63 percent in 1983 to 1.41 percent in 2004 and the percentage of households with negative net worth has risen from 5.04 percent to 6.93 percent.

Several researchers have documented the significant rise in Chapter 7 bankruptcies over the same time period, including Livshits, MacGee, and Tertilt (2006), Athreya (2004), and Sullivan, Warren, and Westbrook (2000), which can easily be seen in Figure (1). Finally, Sullivan, Warren, and Westbrook (2000) also notes that defaults are not only more common but also much larger; median non-mortgage debt-to-income ratio for households filing for bankruptcy doubled *from* 0.75 *to* 1.54 over the period 1981-1997 (see Figure 2, taken from Sullivan, Warren, and Westbrook 2000).

Recent empirical work on consumer credit markets has also documented striking changes in the sensitivity of credit terms to borrower characteristics. A summary of this work is that credit terms, especially for unsecured loans, exhibited little variation across US households as recently as 1990, even though in the cross-section these households exhibited substantial heterogeneity in income, wealth, and default risk.[2] In the subsequent period, from 1990 to the present, a variety of financial contracts, ranging from credit card lines to auto loans to insurance, now exhibit terms that depend nontrivially on regularly updated measures of default risk, particularly a household's credit score. Three related findings stand out from the literature. First, the sensitivity of credit card loan rates to the conditional bankruptcy probability grew substantially after the mid-1990's (Edelberg 2006). Second, credit scores themselves became more informative: Furletti (2003), for example, finds that the spread between the rates paid by highest and lowest risk classifications grew from zero in 1992 to 800 basis points by 2002. Third, the distribution of interest rates for unsecured credit was highly concentrated in 1983 and very diffuse by 2004 (Livshits, MacGee, and Tertilt 2008 and Figure 3); furthermore, the distribution of interest rates for delinquent households was indistinguishable from nondelinquent ones in 1983 but shifted significantly to the right by 2004 (Livshits, MacGee, and Tertilt 2008 and Figure 4).[3]

[1] The data is taken from the Statistical Abstract of the United States, various issues. The figure is from Zagorsky and Lupica (2008). Note that the decline in filings observed in 2006 appears to have been short-lived and that bankruptcy filings are again rising.

[2] A survey of these empirical findings can be found in Hunt (2005).

[3] All interest rate data is taken from the Survey of Consumer Finances. Specifically, the SCF question regarding late payments is "Now thinking of all the various types of debts, were all the payments made the way they were scheduled during the last year, or were payments on any of the loans sometimes made later or missed?" The variable for SCF1983 is "V930" where a value of "1" means "all paid as scheduled" and a value of "5" means"sometimes got behind or missed payments." For SCF2004 the variable is "X3004" where the values of "1" and "5" are the same as for 1983.

The purpose of this paper is to provide a unified story for these facts. Our story is based around the idea that information about borrowers is much better now than it was in the earlier period. Existing work, which we will detail further below, has attempted to account for the observed rise in debt and default. Critically however, these stories all fail along one key dimension: they all fail to reproduce the dispersion and sensitivity increases noted in the previous paragraph. In contrast, we show that improved information is capable of generating precisely the observed changes in the dispersion and sensitivity of credit terms. Thus, while these other factors may have played a role, information changes of the kind we posit must have accompanied them in order for the credit market to have changed from an environment in which heterogeneous borrowers were treated homogeneously to one in which this heterogeneity is explicitly priced.

A good deal of recent attention has been given over to the task of accounting for the rapid growth and relatively high incidence of unsecured indebtedness and bankruptcy. First, there is the possibility that the personal costs incurred by defaulters have fallen substantially, either as a result of improved bankruptcy filing procedures, learning by households from each other about navigating the bankruptcy process, or even lower psychic costs (stigma). Gross and Souleles (2003) argue households did appear to be more willing to default in the late 1990's than in earlier periods, all else equal. Unfortunately, these explanations tend to produce rising default rates combined with declining discharges on average, as households become less able to borrow and therefore default on less debt. A second class of explanations for rising debt and default hinges on the extent to which transactions costs associated with lending are likely to have fallen as a result of improved information storage and processing technologies available to lenders. Athreya (2004) and Livshits, MacGee, and Tertilt (2006) explore this story; unlike changes in costs at the individual level, falling risk-free rates or transactions costs can produce both an increase in default rates and an increase in the amount of debt discharged in bankruptcy, making this mechanism a more promising candidate. Finally, Ellis (1998) argues that usury ceilings played an important role in the rising default rates and indebtedness observed after the 1978 Supreme Court case *Marquette National Bank vs. First Omaha Services Corp.* ruled that only the usury ceiling of the state in which a bank is chartered applies to the terms it offers, not the state in which the customer resides; given that some states (Delaware, South Dakota) had very limited restrictions, usury ceilings effectively ceased to exist. Livshits, MacGee, and Tertilt (2007) dismiss usury ceilings as playing an important role even in the rise in bankruptcy filing rates. Furthermore, the homogeneity of interest rates observed in 1983 – 5 years after the *Marquette* decision – is hard to square with a preeminent role for interest rate ceilings, since the primary issue is why good borrowers did not get discounts.

A common feature of the models that underlie the preceding explanations is full information: the information available to lenders always includes the entire relevant household state vector. In a highly stylized framework, Narajabad (2007) analyzes the effects of an increase in the informativeness of a signal received by lenders on a borrower's long term income level, showing that such a change is qualitatively consistent with the increased indebtedness, increased default, and increased dispersion in loan terms observed. Importantly, Narajabad (2007) features only *ex post* asymmetric information; all contracts are executed under symmetric information. An assumption that both lenders and borrowers are committed to the contract ensures that the *ex post* asymmetric information does not alter equilibrium outcomes. We instead analyze a model in which information is asymmetric between borrowers and lenders and there is no commitment on either side. In this environment, improved information means that lenders can observe more relevant characteristics of borrowers and the lack of commitment implies that any new information is reflected immediately in pricing.

We develop a model that allows for the quantitatively-serious measurement of how unsecured credit markets operate under asymmetric information and how changes in information alter outcomes when loan pricing is individualized. As is well known, equilibria under asymmetric information require a specification of the precise interaction of borrowers and lenders, which we model as a signalling game.[4] We are guided in our choice of market microstructure by the requirement that households perceive a price function for loans as a function of default risk; thus, we need to solve for prices for arbitrary borrowing levels, including those not observed in equilibrium. A second complication that must be dealt with under asymmetric information is the extent to which information is revealed by household decisions. In particular, in a conjectured equilibrium, the information conveyed by a borrower's chosen debt level must not provide incentives for a lender to deviate in the terms offered, given the information available to the intermediary; in our economy, this requirement states that the beliefs used to construct default rates (on the equilibrium path) must be consistent with the stationary distribution produced by the model.

To understand how improvements in information affect outcomes in the credit market, we study two equilibria. First, we allow lenders to observe all relevant aspects of the state vector necessary to predict default risk. We then compare this allocation to one where lenders are no longer able to observe all of these variables. We follow the literature's preferred specification of household labor income over the life-cycle. In this formulation, households draw stochastic incomes that are the sum of four components: a permanent shock realized prior to entry into the labor market (representing formal education), a deterministic age-dependent component with a peak several years before retirement, a persistent shock, and a purely transitory shock.[5] Thus, information changes alter the observability of the components of household labor income; specifically, we prohibit the lenders from observing total income and the two stochastic components while the permanent shock is always observable. The difference across these allocations is a quantitative measure of the effect of improved information about shocks in unsecured credit markets.

Our first set of results focuses on the full information economy, where the pricing of debt incorporates all relevant information from the model. In this case, the bulk of borrowing occurs for life cycle purposes, and the bulk of default occurs when income expectations indicate that future borrowing capacity is not very valuable. As a result, default occurs among the unlucky young, and after age 50 is very low, both of which are features of the data. Under full information, our model matches the default rate and median borrowing on the unsecured credit market, while the ratio of the debt discharged through bankruptcy relative to income is somewhat smaller than the only measure available in the data. Given that we abstract from features that generate large defaults (large uninsured expense shocks and self-employment) the appropriate target for discharged debt is indeed smaller than this statistic (net worth shocks play an important role in Livshits, MacGee, and Tertilt 2006 and Chatterjee *et al.* 2007).[6]

We then demonstrate our central result: moving from full information to a setting where lenders have only partial information produces outcomes consistent with all five features characterizing unsecured credit markets for the bulk of the postwar period. Specifically, equilibrium levels of debt, default, and debt-in-default all fall dramatically, while the sensitivity of credit terms to default risk and discount associated with a clean credit record both virtually disappear. We show constructively that an allocation in which all households can borrow large amounts at the risk-free rate is not an equilibrium: those households with weak future income prospects (high-risk households) have a strong incentive to default at high levels of debt, generating nontrivial default

[4]See Hellwig (1990).

[5]Representative citations include Hubbard, Skinner, and Zeldes (1994) and Krueger and Perri (2006).

[6]While the actual U.S. economy is probably not characterized by full information, at least partly due to regulatory restrictions that we discuss later, the fact that the credit score is essentially the only piece of information needed to forecast default risk likely means the full information assumption is not too unreasonable; see Avery *et al.* (2000) for evidence that scores are highly predictive for default rates.

risk and necessitating a default premium. In turn, as the premium for borrowing is raised, the low-risk households refuse to borrow as much, revealing the type of all those who do; the market then requires a further increase in the interest rate, which reduces borrowing by the high-risk types until they pool again with the low-risk types. This process continues until the incentives to deviate for low-risk borrowers are offset by the need to smooth consumption. As a quantitative matter, this pooling equilibrium occurs at a low enough debt level to sustain risk-free lending to every borrower. These changes, in turn, matter for consumption smoothing and welfare; the near-absence of unsecured credit substantially hinders intertemporal smoothing for the young, especially the skilled (college-educated).[7]

Our results are particularly relevant for another welfare-related question: is more information in the credit market better? A view often asserted in policymaking circles is that better information in the credit market would harm disadvantaged groups, such as racial minorities, that benefit from pooling. Such views have generated strong legislative actions as well.[8] Our model predicts that all agents are better off under full information, as every individual can borrow more at lower rates. We also show that better information will lead to both "democratization" and "intensification" of credit – that is, we obtain increases in both the extensive and intensive margins of the unsecured credit market. In terms of welfare, the intensification is quantitatively more significant: high school educated agents benefit less than college educated agents under full information, mainly because they are less-constrained by low information since their desire to borrow is limited by relatively-flat expected age-income profiles. Thus, a move to full information does not redistribute credit from bad to good borrowers, it expands it for everyone (as in the classic lemons problem). The key policy implication we derive from the model is that the government should not try to reverse the increase in bankruptcies; it is the result of welfare-improving improvements in the information available to credit markets. In particular, high filing rates reflect the improved ability of households to borrow against an uncertain future, while high dispersion in interest rates reflect the fact that many who once were effectively credit-rationed are no longer limited in this way. However, despite the overall welfare gains from full information, all agents in the economy would be willing to rid themselves of the bankruptcy option *ex ante*; thus, our findings suggest that policymakers should focus on how to make the bankruptcy option less attractive not because it has recently gotten more prevalent but because it is likely to have *always* been welfare-reducing.

Our paper is related to theoretical work of Chatterjee, Corbae, and Ríos-Rull (2008b), which attempts to provide a theory of reputation in unsecured borrowing; relative to that paper we simplify matters by limiting the dynamic aspects of credit terms.[9] Our justification for this approach is that under full information credit scores are irrelevant, while our interpretation of the period of partial information as the 1980s implies that credit scores were not used even though they were collected; in turn, a key payoff of this assumption is quantitative tractability. Our paper is also related to Sánchez (2008), who studies a screening model of unsecured credit but abstracts from life-cycle considerations. Given the clear life-cycle aspect of both unsecured borrowing and bankruptcy, we focus on precisely capturing the interaction of information asymmetries with life-cycle earnings growth. Lastly, our work is complementary to Livshits, MacGee, and Tertilt (2007b)

[7]Berger, Frame, and Miller (2005) show that the widespread use of credit scoring in the small business market has been associated with more borrowing and higher default rates, consistent with our model.

[8]Specifically, Section 215 of FACT Act directs the Federal Reserve Board, the Federal Trade Commission, and the Office of Fair Housing and Equal Opportunity (a department of HUD) to study whether "the consideration or lack of consideration of certain factors...could result in negative treatment of protected classes under the Equal Credit Opportunity Act." "Report to Congress on Credit Scoring and Its Effects on the Availability and Affordability of Credit," Board of Governors of the Federal Reserve System, August 2007.

[9]See also Chatterjee, Corbae, and Ríos-Rull (2008a).

and Drozd and Nosal (2007), who offer theories of increased differentiation of borrowers based on declining contracting costs, but abstract from asymmetric information.[10]

2 A Model with Default

Households in the model economy live for a maximum of $J < \infty$ periods. There are two classes of households – "normals", who face uninsurable risk, save and borrow via costly financial intermediaries, and occasionally choose to file for bankruptcy, and "specials", who do not face idiosyncratic risk, do not default, and earn higher rates of return arising from direct ownership of physical capital.

2.1 Normal Households

Each normal household of age j has a probability $\psi_j < 1$ of surviving to age $j+1$ and has a pure time discount factor $\beta < 1$. Households value consumption and attach a negative value λ_j (in utility terms) to all nonpecuniary costs of filing for bankruptcy. Their preferences are represented by the expected utility function

$$\sum\nolimits_{j=1}^{J} \sum\nolimits_{s^j} \left(\prod\nolimits_{i=0}^{j} \beta \psi_{j,y} \right) \Pi\left(s^j\right) \left[\frac{n_j}{1-\sigma} \left(\frac{c_j}{n_j} \right)^{1-\sigma} - \lambda_j \mathbf{1}\left(d_j = 1\right) \right], \tag{1}$$

where $d_j = 1$ if the household chooses to default. $\Pi\left(s^j\right)$ is the probability of a given history of events s^j, $\sigma \geq 0$ is the Arrow-Pratt coefficient of relative risk aversion, and n_j is the number of household members at age j. We assume that households retire exogenously at age $j^* < J$.

The existence of nonpecuniary costs of bankruptcy λ are suggested by the calculations in Fay, Hurst, and White (1998) that a large measure of households would have "financially benefited" from filing for bankruptcy but did not. Furthermore, Gross and Souleles (2002) and Fay, Hurst, and White (1998) document significant unexplained variability in the probability of default across households, even after controlling for a large number of observables. These results imply the presence of implicit unobserved collateral that is heterogeneous across households; λ reflects any such unobserved collateral, including (but not limited to) any stigma associated with bankruptcy. However, it also reflects a large number of other costs that are not explicitly pecuniary in nature (as in Athreya 2002), such as the added search costs associated with renting apartments when one does not have clean credit.

We allow creditors to track the history of default via a binary marker $m = \{0, 1\}$, where $m = 1$ indicates the presence of bankruptcy in a borrower's past and $m = 0$ implies no record of past default. This marker will be removed probabilistically to capture the effect of current regulations requiring that a bankruptcy filing disappear from one's credit score after 10 years and agents are prohibited from declaring Chapter 7 bankruptcy more than once every 7 years.[11] We denote by the parameter $\xi \in (0, 1)$ the likelihood of the bad credit market disappearing tomorrow. Under partial information, the price charged a household for issuing debt will in general depend on m, so that households with recent defaults will receive different credit terms than households with 'clean' credit.

[10]Similar to Narajabad (2007), both papers also assume strong *ex post* commitment to contracts on the part of lenders.

[11]Some households in our model will be able to declare bankruptcy more than once every 7 years. Since households in the US economy also have the option to declare Chapter 13 and typically have few non-exempt assets, this outcome is reasonable and avoids the need for the cumbersome state variable of "the number of periods since a filing".

The household budget constraint during working age is given by

$$c_j + q\left(b_j, I\right) b_j + \mathbf{\Delta 1}\left(d_j = 1\right) \leq a_j + \left(1-\tau\right) W \omega_{j,y} y e \nu, \tag{2}$$

where q is an individual-specific bond price that depends on bond issuance b_j and a vector of individual characteristics I, a is net worth, Δ is the pecuniary cost of filing for bankruptcy, and the last term is after-tax current income. Log labor income is the sum of five terms: the aggregate wage index W, a permanent shock y realized prior to entry into the labor market, a deterministic age term $\omega_{j,y}$, a persistent shock e that evolves as an AR(1)

$$\log\left(e'\right) = \rho \log\left(e\right) + \epsilon', \tag{3}$$

and a purely transitory shock $\log(\nu)$. Both ϵ and $\log(\nu)$ are independent mean zero normal random variables with variances that are y-dependent. The budget constraint during retirement is

$$c_j + q\left(b_j, I\right) b_j \leq a_j + \theta W \omega_{j^*-1,y} y e_{j^*-1} \nu_{j^*-1} + \Theta W, \tag{4}$$

where for simplicity we assume that pension benefits are a composed of a fraction $\theta \in (0,1)$ of income in the last period of working life plus a fraction Θ of average income (which is normalized 1). Because bankruptcy is not a retiree phenomenon, we deliberately keep the specification of retirees simple. There do not exist markets for insurance against income or survival risk and we abstract from any sources of long-run growth.

The survival probabilities $\psi_{j,y}$ and the deterministic age-income terms $\omega_{j,y}$ differ according to the realization of the permanent shock. We interpret y as differentiating between non-high school, high school, and college education levels, as in Hubbard, Skinner, and Zeldes (1994), and the differences in these life-cycle parameters will generate different incentives to borrow across types. In particular, college workers will have higher survival rates and a steeper hump in earnings; the second is critically important as it generates a strong desire to borrow early in the life cycle, exactly when default is highest. The life-cycle aspect of our model is key – in the data, defaults are skewed toward young households (who borrow at least in part for purely intertemporal reasons).

2.1.1 Recursive Formulation

The recursive version of the household problem is useful for understanding the default decision. A household of age j with good credit $m = 0$ solves the dynamic programming problem

$$v\left(a, y, e, \nu, \lambda, j, m=0\right) = \max_{b, d(e', \nu', \lambda') \in \{0,1\}} \left\{ \begin{array}{c} \frac{n_j}{1-\sigma}\left(\frac{c_j}{n_j}\right)^{1-\sigma} + \beta \psi_{j,y} \sum_{e', \nu', \lambda'} \pi_e\left(e'|e\right) \pi_\nu\left(\nu'\right) \pi_\lambda\left(\lambda'|\lambda\right) \\ \times \left[\begin{array}{c} \left(1 - d\left(b, e', \nu', \lambda'\right)\right) v\left(b, y, e', \nu', \lambda', j+1, m'=0\right) + \\ d\left(b, e', \nu', \lambda'\right) v^D\left(0, y, e', \nu', \lambda', j+1, m'=1\right) \end{array} \right] \end{array} \right\} \tag{5}$$

where

$$v^D\left(0, y, e', \nu', \lambda', j+1, m'=1\right) = \left\{ \begin{array}{c} \frac{n_j}{1-\sigma}\left(\frac{c_j}{n_j}\right)^{1-\sigma} - \lambda + \beta \psi_{j,y} \sum_{e', \nu', \lambda'} \pi_e\left(e'|e\right) \pi_\nu\left(\nu'\right) \pi_\lambda\left(\lambda'|\lambda\right) \\ \times \left[\begin{array}{c} \xi v\left(a', y, e', \nu', \lambda', j+1, m'=0\right) + \\ \left(1-\xi\right) v\left(a', y, e', \nu', \lambda', j+1, m'=1\right) \end{array} \right] \end{array} \right\} \tag{6}$$

is the value of default; note that households cannot borrow or save during the period in which they declare bankruptcy. A household that is currently flagged with bad credit $m = 1$ solves the problem

$$v\left(a,y,e,\nu,\lambda,j,m=1\right)=\max_{b,d(e',\nu',\lambda')\in\{0,1\}}\left\{\begin{array}{c}\frac{n_j}{1-\sigma}\left(\frac{c_j}{n_j}\right)^{1-\sigma}+\beta\psi_{j,y}\sum_{e',\nu',\lambda'}\pi_e\left(e'|e\right)\pi_\nu\left(\nu'\right)\pi_\lambda\left(\lambda'|\lambda\right)\\ \times\left[\begin{array}{c}\xi\left[\begin{array}{c}\left(1-d\left(b,e',\nu',\lambda'\right)\right)v\left(b,y,e',\nu',\lambda',j+1,m'=0\right)+\\ d\left(b,e',\nu',\lambda'\right)v^D\left(0,y,e',\nu',\lambda',j+1,m'=1\right)\end{array}\right]+\\ \left(1-\xi\right)\left[\begin{array}{c}\left(1-d\left(b,e',\nu',\lambda'\right)\right)v\left(b,y,e',\nu',\lambda',j+1,m'=1\right)+\\ d\left(b,e',\nu',\lambda'\right)v^D\left(0,y,e',\nu',\lambda',j+1,m'=1\right)\end{array}\right]\end{array}\right]\end{array}\right. \tag{7}$$

In each period the household initially makes a consumption-savings decision (c,b), where b is the amount of borrowing/saving. The household also makes a conditional default decision $d\left(b,e',\nu',\lambda'\right)$ that equals 1 if the household declares bankruptcy in the event that next period's shocks are $\left(e',\nu',\lambda'\right)$ and 0 otherwise.

2.2 Loan Pricing

We focus throughout on competitive lending. There exists a competitive market of intermediaries who offer one-period debt contracts and utilize available information to offer individualized credit pricing. Let I denote the information set for a lender and $\widehat{\pi}^b$: $b_{|I}\rightarrow[0,1]$ denote the function that assigns a probability of default to a loan of size b given information I. $\widehat{\pi}^b$ is identically zero for positive levels of net worth and is equal to 1 for some sufficiently large debt level. The break-even pricing function must satisfy

$$q\left(b,I\right)=\begin{cases}\frac{1}{1+r} & \text{if } b\geq 0\\ \frac{\left(1-\widehat{\pi}^b\right)\psi_j}{1+r+\phi} & \text{if } b<0\end{cases} \tag{8}$$

given $\widehat{\pi}^b$. r is the exogenous risk-free saving rate and ϕ is a transaction cost for lending, so that $r+\phi$ is the risk-free borrowing rate; the pricing function takes into account the automatic default by those households that die at the end of the period. With full information, a variety of pricing arrangements will lead to the same price function. However, as is well known (Hellwig 1990), under asymmetric information settings outcomes often depend on the particular "microstructure" being used to model the interaction of lenders and borrowers. Under full information our approach is completely standard (see Chatterjee *et al.* 2007 or Livshits, MacGee, and Tertilt 2006), as we employ a setting that delivers to households a function $q\left(b,y,e,\nu,j,m\right):b\rightarrow\left[0,\frac{1}{1+r}\right]$ that they can take parametrically when optimizing; the compactness of the range for q implies that the household problem has a compact opportunity set and therefore possesses a solution.

We now detail explicitly the microstructure that underlies our pricing function, which we model as a two-stage game between borrowers and lenders. In the first stage, borrowers name a level of debt b that they wish to issue. Second, a continuum of lenders compete in an auction where they simultaneously post a price for the desired debt issuance of the household and are committed to delivering the amount b in the event their "bid" is accepted; that is, the lenders are engaging in Bertrand competition for borrowers. In equilibrium borrowers choose the lender who posts the lowest interest rate (highest q) for the desired amount of borrowing. Thus, households view the pricing functions as schedules and understand how changes in their desired borrowing will alter the terms of credit (that is, they know $D_bq\left(b,I\right)$) because they compute the locus of Nash equilibria under price competition. Exactly how the pricing function depends on the components in I will be specified next. We defer a formal statement of equilibrium until after our discussion of q.

2.2.1 Full Information

In the full information case, I includes all components of the household state vector: $I = (a, y, e, \nu, \lambda, j, m)$. Zero profit for the intermediary requires that the probability of default used to price debt must be consistent with that observed in the stationary equilibrium, implying that

$$\widehat{\pi}^b = \sum\nolimits_{e',\nu',\lambda'} \pi_e\left(e'|e\right)\pi_\nu\left(\nu'\right)\pi_\lambda\left(\lambda'|\lambda\right)d\left(b\left(a,y,e,\nu,\lambda,j,m\right),e',\nu',\lambda'\right). \tag{9}$$

Since $d\left(b, e', \nu', \lambda'\right)$ is the probability that the agent will default in state $\left(e', \nu', \lambda'\right)$ tomorrow at debt level b, integrating over all such events *tomorrow* is the relevant default risk. This expression also makes clear that knowledge of the persistent component e is critical for predicting default probabilities; the more persistent e is, the more useful it becomes in assessing default risk.[12] With partial information we will need to integrate over current states as well as future ones, since pieces of the state vector will not be observable.

2.2.2 Partial Information

The main innovation of this paper is to take a first step in evaluating the consequences of changes in the information available for predicting default risk on one-period debt. Default risk, in turn, arises from a combination of indebtedness and the risk associated with future income. Under asymmetric information, we make an anonymous markets assumption: no past information about an individual (other than their current credit market status m) can be used to price credit. This assumption rules out the creation of a credit score that encodes past default behavior through observed debt levels; since income shocks are persistent, past borrowing would convey useful information, although it is an open question how much. Given the difficulties encountered by other researchers in dealing with dynamic credit scoring, we think it useful to consider an environment for which we can compute equilibria.

Partial information in our economies will manifest itself through the observability of the stochastic elements of the household state vector. We maintain the assumption throughout that age and education are observable and that total income and the transitory and persistent components of income are not.[13] In addition, we do not let lenders observe the current net worth of the borrower, total current income, and the current stigma cost. Therefore, we have $I = (y, j, m)$ (with (a, e, ν, λ) not observed).[14] Since the observables (age and education) are slow-moving components of the individual state vector, our assumptions avoid overstating the power of adverse selection to unravel credit market arrangements.[15]

The first concern for solving the partial information economy is that lenders must hold beliefs over the probability of an individual being in a particular state (e, ν, λ) given *whatever* is observed, knowing also that what is observed is a function of lenders' *a priori* beliefs; that is, beliefs must satisfy a fixed point condition. Let $\Pr(e, \nu, \lambda | b, y, j, m)$ denote the probability that an individual's

[12] We leave as future work the case where neither borrowers nor lenders know how to decompose their income changes, as in the original permanent income model of Friedman (1957).

[13] Again, we note that regulatory restrictions prohibit the use of age in determining credit terms, at least in the unsecured credit market, along with race and gender. We study the possibility that types are unobserved in a companion paper, which focuses on estimating the costs of such regulations.

[14] We separate b from I even though b is observable because the borrower takes the derivative of q with respect to b and it is therefore more convenient to make it a separate argument.

[15] We briefly examined a case where total indebtedness is also not observed; since the game underlying that arrangement is considerably more difficult to specify, we leave a complete study of that economy to future work. Our preliminary results suggest that default actually rises under partial information, making that setup inconsistent with empirical observations.

shock vector in any period takes a given value (e, v, λ), conditional on observing the size of borrowing, the permanent shock, age, and credit status. Given this assessment, the lender can compute the likelihood of default on a loan of size b:

$$\widehat{\pi}^b = \sum\nolimits_{e,\nu,\lambda} \left[\sum\nolimits_{e',\nu',\lambda'} \pi_e\left(e'|e\right) \pi_\nu\left(\nu'\right) \pi_\lambda\left(\lambda'|\lambda\right) d\left(b, e', \nu', \lambda'\right) \right] \Pr\left(e, \nu, \lambda | b, y, j, m\right). \tag{10}$$

In a stable environment with a small number of creditors, or one with an efficient technology for information sharing, intermediaries must form beliefs that incorporate everything they either know or can infer from observables; competitors who exploit this information may be able to 'cream-skim' the best borrowers away from those who form beliefs in any other way.[16] We view the partial information setting as a natural analogue to the conditions that prevailed in the early 1980s, for reasons that will become clear later. Figure (5) illustrates the inference problem of the intermediary – for a given level of borrowing there may exist several different individuals who could be issuing that b. $\Pr(e, \nu, \lambda | b, y, j, m)$ assigns a probability to each of these types based on knowledge of the decision rules of agents.

In the partial information environment the calculation of $\Pr(e, \nu, \lambda | b, y, j, m)$ is nontrivial, because it involves the distribution of endogenous variables. First, let the invariant distribution over states be denoted by $\Gamma(a, y, e, \nu, \lambda, j, m)$. In a stationary equilibrium the joint conditional probability density over shocks (e, v, λ) must be given by

$$\Pr\left(e, \nu, \lambda | b, y, j, m\right) = \int_a \Gamma\left(a = f\left(b, y, e, \nu, \lambda, j, m\right), y, e, \nu, \lambda, j, m\right), \tag{11}$$

where f is the inverse of g with respect to the first argument wherever $\Gamma(a, y, e, \nu, \lambda, j, m) > 0$; that is,

$$a = f\left(b, y, e, \nu, \lambda, j, m\right)$$

and

$$b = g\left(a, y, e, \nu, \lambda, j, m\right).$$

Thus, the decision rule of the household under a given pricing scheme is inverted to infer the state conditional on borrowing. Using this function the intermediary then integrates over the stationary distribution of net worth, conditional on observables, and uses this density to formulate beliefs.

It is possible that intermediaries in the partial information world would find it profitable to offer a menu of contracts and separate types (meaning agents with different realizations of the shocks (e, ν, λ)) in this manner. We restrict attention to the pure signaling model, which is not only tractable but also consistent with the relative homogeneity of unsecured loan contracts prior to 1990, and thus do not permit screening through multiple contracts.[17]

2.2.3 Off-Equilibrium Beliefs

In addition to ensuring that pricing reflects equilibrium information transmission, the second key complication present under asymmetric information is how to assign beliefs about a household's

[16] This point is related to the extensive survival literature, which investigates whether agents who form beliefs that deviate from rational expectations can survive in asset markets.

[17] In our set-up, borrowers (who are informed) move first. In contrast to screening (where the uninformed move first), our approach not only generates sensible predictions – as we will show later – but aids tractability as well. This is because when borrowers optimize subject to a known mapping from arbitrary borrowing levels to loan prices, they are automatically checking all relevant deviations. In contrast, in a screening game the uninformed players (lenders) move first, which necessitates checking for deviations in the infinite-dimensional space of all alternative pricing functions. Sánchez (2008) models the screening game and obtains some homogeneity by assuming that the cost of a screening contract is too high in the earlier period for it to be used.

state for values of the state *not* observed in equilibrium. That is, how should lenders assign beliefs regarding repayment by households where $\Gamma(a, y, e, \nu, \lambda, j, m) = 0$? This issue matters because a household's decision on the equilibrium path depends on its understanding of lender behavior at *all* feasible points in the state space, including those that never arise. Our theory does not restrict off-equilibrium beliefs in a clear way, since we require only zero profit on the equilibrium path, so we must specify a rule for off-equilibrium outcomes. Given the proliferation of equilibria typically present in signaling models, we want to discipline this choice as tightly as possible.

The assignment of off-equilibrium beliefs turns out to be closely related to the algorithm we use to compute equilibria. Our algorithm is iterative – we guess pricing functions, compute implied default rates, recompute pricing functions based on the new default rates, and iterate to convergence. The critical choice of the algorithm is therefore the initial pricing function and the rule for updating. We assign the initial off-equilibrium beliefs in order to minimize the effects on equilibrium outcomes; specifically, we begin by guessing a pricing function q^0 with the following properties: it is constant at the risk-free borrowing rate $\frac{1}{1+r+\phi}$ over the range $[0, b_{\min})$, where $b_{\min}$ is a debt level such that no agent could prevent default if he borrowed that much, and then drops to 0 discontinuously. The implied beliefs for the intermediary are such that default never occurs except when it *must* in every state of the world; this assumption has the appeal that it is very weak requirement, as no equilibrium pricing function could possibly permit more borrowing. Since our algorithm will generate a monotone mapping over pricing functions, it is imperative that we begin with this function if we are to avoid limiting credit opportunities unnecessarily. It is useful to compare our initial pricing function with the natural borrowing limit, the limit implied by requiring consumption to be positive with probability 1 in the absence of default. Our initial debt limit is larger than the natural borrowing limit, as agents can use default to keep consumption positive in some states of the world; we only require that they not need to do this in every state of the world.[18] We also restrict attention to weakly monotone functions, for reasons to be detailed below.

2.2.4 Equilibrium

We now formally define an equilibrium for the game between borrowers and lenders. We denote the state space for households by $\Omega = \mathcal{B} \times \mathcal{Y} \times \mathcal{E} \times \mathcal{V} \times \mathcal{L} \times \mathcal{J} \times \{0,1\} \subset \mathcal{R}^4 \times \mathcal{Z}_{++} \times \{0,1\}$ and space of information as $\mathcal{I} \subset \mathcal{Y} \times \mathcal{E} \times \mathcal{V} \times \mathcal{L} \times \mathcal{J} \times \{0,1\}$.

Definition 1 *A Perfect Bayesian Equilibrium for the credit market consists of (i) household strategies for borrowing* $b^* : \Omega \to \mathcal{R}$ *and default* $d^* : \Omega \times \mathcal{E} \times \mathcal{V} \to \{0,1\}$ *and intermediary strategies for lending* $q^* : \mathcal{R} \times \mathcal{I} \to \left[0, \frac{1}{1+r}\right]$ *and (ii) beliefs about the borrower state* Ω *given borrowing* $\mu^*(\Omega|b)$, *that satisfy the following:*

1. ***Lenders optimize**: Given beliefs* $\mu^*(\Omega|b)$, q^* *is the pure-strategy Nash equilibrium under price competition.*
2. ***Households optimize**: Given prices* $q^*(b, I)$, b^* *solves the household problem.*
3. ***Beliefs are consistent with Bayes' rule**: The stationary joint density of* Ω *and* b, $\Gamma_{\mu^*}(\Omega, b)$, *that is induced by (i) lender beliefs and the resultant optimal pricing, (ii) household optimal borrowing strategies, and (iii) the exogenous process for earnings shocks and mortality, is such that the associated conditional distribution of* Ω *given* b, *denoted* $\Gamma^b_{\mu^*}(b)$, *is* $\mu^*(\Omega|b)$.

[18] This point is also made in Chatterjee *et al.* (2007).

4. ***Off-Equilibrium Beliefs:*** *$q^*(b, I) = 0$ $\forall b$ such that $\Gamma^b_{\mu^*}(b) = 0$ and $q^*(b, I)$ is weakly decreasing in b.*

If our shocks are continuous random variables, the debt levels that get zero weight in the stationary distribution are those above and below any levels that get positive weight (Γ has a connected support); with discrete random variables we do not get connectedness, but we solve the model as if it obtained. Obviously, for default decisions the upper limit is irrelevant; thus, as noted above, we are imposing a belief about the behavior of agents who borrow more than *any* agent would in equilibrium, no matter what unobserved state they are currently in. Given that q is weakly decreasing in b, the natural assumption is that this agent intends to default with probability one.

2.2.5 Computing Partial Information Equilibria

The imposition of conditions on beliefs off-the-equilibrium path makes the computational algorithm we employ relevant for outcomes, and in this section we therefore discuss in some detail our algorithm for computing partial information competitive equilibria. The computation of the full information equilibrium is straightforward using backward induction; since the default probabilities are determined by the value function in the next period, we can solve for the entire equilibrium, including pricing functions, with one pass. The partial information equilibrium is not as simple, since the lender beliefs regarding the state of borrowers influence decisions and are in turn determined by them; an iterative approach is therefore needed.

1. Guess the initial function $q^0(b, y, j, m)$ discussed above;
2. Solve household problem to obtain $g(a, y, e, \nu, \lambda, j, m)$, $f(b, y, e, \nu, \lambda, j, m)$, and $d(e', \nu', \lambda' | a, y, e, \nu, \lambda, j, m)$;
3. Compute $\Gamma(a, y, e, \nu, \lambda, j, m)$ and $P(b, y, e, \nu, \lambda, j, m) = \Gamma(f(b, y, e, \nu, \lambda, j, m), y, e, \nu, \lambda, j, m)$;
4. Locate $b_{\min}(y, e, \nu, \lambda, j, m)$, the minimum level of debt observed conditional on the other components of the state vector;
5. Set $q^*(b \le b_{\min}, y, j, m) = 0$ (that is, borrowing that exceeds any observed triggers default with probability 1);
6. Compute
$$\pi^d(b, y, e, \nu, \lambda, j, m) = \sum\nolimits_{e'} \sum\nolimits_{\nu'} \sum\nolimits_{\lambda'} \pi_e(e'|e)\, \pi_\nu(\nu')\, \pi_\lambda(\lambda'|\lambda)\, d(e', \nu', \lambda'); \tag{12}$$
7. Compute $\Pr(e, \nu, \lambda | b, y, j, m)$ from $P(b, y, e, \nu, \lambda, j, m)$ for each (b, y, j, m), the probability that an individual is in (e, ν, λ) given observed (b, y, j, m);
8. Compute
$$\widehat{\pi}^d(b, y, j, m) = \sum\nolimits_{e} \sum\nolimits_{\nu} \sum\nolimits_{\lambda} \pi^d(b, y, e, \nu, \lambda, j, m) \Pr(e, \nu, \lambda | b, y, j, m), \tag{13}$$
the expected probability of default for an individual in observed state (b, y, j, m);
9. Set
$$q^*(b, y, j, m) = \frac{\left(1 - \widehat{\pi}^d(b, y, j, m)\right)\psi_j}{1 + r + \phi} \quad \text{for all } b \ge b_{\min}(b, y, j, m); \tag{14}$$

10. Set

$$q^1(b,y,j,m) = \Xi q^0(b,y,j,m) + (1-\Xi)\, q^*(b,y,j,m)$$

and repeat until the pricing function converges, where Ξ is set very close to 1.

Because the household value function is continuous but not differentiable or concave, we solve the household problem on a finite grid for a, using linear interpolation to evaluate it at points off the grid. Similarly, we use linear interpolation to evaluate q at points off the grid for b. To compute the optimal savings behavior we use golden section search (see Press *et al.* 1993 for details of the golden section algorithm) after bracketing with a coarse grid search; we occasionally adjust the brackets of the golden section search to avoid the local maximum generated by the nonconcave region of the value function. To calibrate the model we use a derivative-free method to minimize the sum of squared deviations from the targets; the entire program is implemented using OpenMP instructions over 8 processors.

Let $\mathcal{Q}$ denote the compact range of the pricing function q; as noted above, $\mathcal{Q}$ is a compact subset of the unit interval. Our iterative procedure maps the lattice of weakly-monotone continuous functions over $\mathcal{Q}$ back into itself. To ensure the existence of a unique fixed point for this mapping, we would want to establish the contraction property for this mapping; however, once the price at a particular point reaches zero it can never become positive, so the contraction property will not hold. As a result, both the initial condition and the updating scheme could matter for outcomes (since the equilibrium pricing function may not be unique). We have detailed above our approach for selecting the initial condition and the updating procedure; we then set Ξ close enough to 1 that the iterative procedure defines a monotone mapping, ensuring the existence of at least one fixed point.[19] $q = 0$ is also an equilibrium under certain restrictions on lender beliefs, and is a fixed point of our iterative procedure; if no agent receives any current consumption for issuing debt and lenders' off-equilibrium beliefs are that any debt will be defaulted upon with probability 1, no debt is issued, intermediaries make zero profit while acting optimally. The key advantage of our initial condition is that it guarantees convergence to the competitive equilibrium which supports the largest amount of borrowing – formally, it generates a descending Kleene chain on the lattice.[20]

Our interest in the equilibrium which permits the most borrowing at the lowest rates arises from the fact that such an equilibrium Pareto-dominates all the others (conditional on the monotonicity restriction). In our economy all pricing is individualized and r is effectively exogenous (at least with respect to the unsecured credit market), meaning that the decisions of one type do not impose pecuniary externalities on any other type. Thus, we can analyze the efficiency of an allocation individual-by-individual (in an *ex ante* sense). For any individual, the outcome under q^0 dominates any other, whether they exercise the default option or not, because it maximizes the amount of consumption-smoothing that an individual could achieve. Since q is a monotone-decreasing function of b, it follows that any allocation which generates higher q for each b dominates one with lower q; that is, $q_1 \succeq q_2$ (with the natural ordering for functions) implies that allocation 1 Pareto-dominates allocation 2. Since $q = 0$ is the "worst" equilibrium in the sense that no borrowing is permitted at all, any equilibrium with positive borrowing at finite rates must yield higher *ex ante* social welfare.

[19] Our results are the same if we set $\Xi \in [0.95, 0.999]$. Because of the slow updating the program typically takes several days to converge.

[20] We know of no conditions that guarantee the existence of a fixed point other than $q = 0$; however, because $\Delta > 0$ the equilibria we compute always satisfy $q > 0$. Kleene chains are discussed in Kleene (1952).

2.3 Special Households

It is well known (e.g. Budría Rodríguez *et al.* 2002) that within a very broad class on consumption-savings models, labor income processes estimated from panel data are incapable of generating the extremely high degree of wealth concentration observed in the data. Specifically, parameters that allow the model to match average wealth will typically lead to counterfactually-high wealth levels for most households. Because we wish to accurately accommodate debt use and the general equilibrium effects arising from changes in information, we require our model to capture both wealth concentration *and* overall wealth levels. We therefore posit a class of "special" households of measure μ_s who face neither idiosyncratic risk nor financial market frictions and therefore earn a higher rate of return on savings. In equilibrium, these households will generate high concentrations of wealth and will never default. Their present-value budget constraint is

$$\sum_{j=1}^{J} \left(\frac{1}{1 + MPK - \delta} \right)^{j-1} c_j = A_1 \tag{15}$$

where lifetime wealth is given by

$$\begin{aligned} A_1 \quad = \quad & k_1 + \sum_{j=1}^{j^*-1} \left(\frac{1}{1 + MPK - \delta} \right)^{j-1} (1 - \tau)\, wy\omega_{j,y} + \\ & \left(\frac{1}{1 + MPK - \delta} \right)^{j^*-1} \sum_{j=j^*}^{J} \left(\frac{1}{1 + MPK - \delta} \right)^{j-j^*-1} (\theta wy\omega_{j^*-1,y} + \Theta)\,; \end{aligned} \tag{16}$$

we assume that special households are drawn from the measure of college types only. We set preferences to logarithmic for these households. These assumptions imply that we can solve for their decisions analytically:

$$c_1 = \frac{1 - \beta_s}{1 - \beta_s^J} A_1 \tag{17}$$

$$c_j = \beta_s^j (1 + MPK - \delta)^{j-1} c_1. \tag{18}$$

Capital holdings are then given by the budget constraint at each age:

$$k_{j+1} = (1 + MPK - \delta)\, k_j + (1 - \tau)\, wy\omega_{j,y} - \frac{1 - \beta_s}{1 - \beta_s^J} \beta^{j-1} (1 + MPK - \delta)^j A_1. \tag{19}$$

The presence of the special households means that the risk-free rate is almost independent of bankruptcy policy.

2.4 Government

The only purpose of government in this model is to fund pension payments to retirees. The government budget constraint is

$$\begin{aligned} & \tau (1 - \mu_s)\, W \int y\omega_{j,y} e\nu \Gamma (a, y, e, \nu, \lambda, j < j^*, m) + \tau \frac{\mu_s}{J} W \sum_{j=1}^{j^*-1} y\omega_{j,y} \\ = \quad & (1 - \mu_s)\, W \int (\theta\omega_{j^*-1,y} y e_{j^*-1} \nu_{j^*-1} + \Theta)\, \Gamma (a, y, e, \nu, \lambda, j \geq j^*, m) + \frac{\mu_s}{J} W \sum_{j=1}^{j^*-1} (\theta\omega_{j^*-1,y} y + \Theta)\,. \end{aligned} \tag{20}$$

2.5 Production Firms

A continuum of production firms rent capital and labor to produce output using the technology

$$Y = K^{\alpha} N^{1-\alpha} - \delta K. \tag{21}$$

Due to constant returns to scale these firms earn zero profit and we can normalize the number of firms to 1.

2.6 Market Clearing

The market for loans clears when the risk-free saving rate equals the marginal product of capital net of depreciation δ:

$$r = \alpha K^{\alpha-1} N^{1-\alpha} - \delta - \vartheta, \tag{22}$$

where ϑ is an intermediation cost that applies to both saving and borrowing. Total capital is the unique positive solution to

$$\begin{aligned} K \;=\; & \frac{1-\mu_s}{1+\alpha K^{\alpha-1} N^{1-\alpha} - \delta - \vartheta} \int b\left(a, y, e, \nu, \lambda, j, m\right) \Gamma\left(a > 0, y, e, \nu, \lambda, j, m\right) + \\ & \frac{1-\mu_s}{1+\alpha K^{\alpha-1} N^{1-\alpha} - \delta - \vartheta + \phi} \int \Big(1 - \pi^b\left(a, y, e, \nu, \lambda, j, m\right)\Big) b\left(a, y, e, \nu, \lambda, j, m\right) \Gamma\left(a < 0, y, e, \nu, \lambda, j, m\right) + \\ & \frac{\mu_s}{J} \sum_{j=1}^{J} k_j \end{aligned} \tag{23}$$

where

$$N = (1-\mu_s) \int y \omega_{j,y} e \nu \Gamma\left(a, y, e, \nu, \lambda, j, m\right) + \frac{\mu_s}{J} \sum_{j=1}^{j^*-1} y \omega_{j,y} \tag{24}$$

is total labor input and $\alpha \in (0,1)$ is the elasticity of output with respect to capital. The labor market clears when the aggregate wage index equals the marginal product of labor:

$$W = (1-\alpha) K^{\alpha} N^{-\alpha}. \tag{25}$$

Finally, the goods market clears when total consumption plus total transactions costs equals total output less depreciation:

$$C = (1-\mu_s) \int c \Gamma\left(a, y, e, \nu, \lambda, j, m\right) + \frac{\mu_s}{J} \sum_{j=1}^{J} c_j \tag{26}$$

$$T = (1-\mu_s) \int \left[\phi \mathbf{1}\left(b < 0\right) b + \Delta \mathbf{1}\left(d = 1\right) + \vartheta b\right] \Gamma\left(a, y, e, \nu, \lambda, j, m\right) \tag{27}$$

$$C + T = K^{\alpha} N^{1-\alpha} - \delta K, \tag{28}$$

where $\mathbf{1}\left(A\right)$ is the indicator function for set A. This expression can be obtained by summing over the budget constraints and imposing the optimality conditions for intermediaries and production firms; by Walras' law we can ignore it.

3 Calibration

We set $\sigma = 2$. We set $\theta = 0.35$ at an exogenous retirement (model) age of 45 and $\Theta = 0.2$, yielding an overall replacement rate around 55 percent. The income process is taken from Hubbard, Skinner, and Zeldes (1994), which estimates separate processes for non-high school, high school, and college-educated workers for the period 1982-1986.[21] Figure (6) displays the path for $\omega_{j,y}$ for each type; the large hump present in the profile for college-educated workers implies that they will want to borrow early in life to a greater degree than the other types will (despite their effective discount factor being somewhat higher because of higher survival probabilities). The process is discretized with 15 points for e and 3 points for ν. The resulting processes are

$$\begin{aligned} \log(e') &= 0.95 \log(e) + \epsilon' \\ \epsilon &\sim N(0, 0.033) \\ \log(\nu) &\sim N(0, 0.04) \end{aligned}$$

for non-high school agents,

$$\begin{aligned} \log(e') &= 0.95 \log(e) + \epsilon' \\ \epsilon &\sim N(0, 0.025) \\ \log(\nu) &\sim N(0, 0.021) \end{aligned}$$

for high school agents, and

$$\begin{aligned} \log(e') &= 0.95 \log(e) + \epsilon' \\ \epsilon &\sim N(0, 0.016) \\ \log(\nu) &\sim N(0, 0.014) \end{aligned}$$

for college agents; the measures of the three groups are 15, 58, and 22 percent, respectively, and the measure of special agents is $\mu_s = 0.05$.[22] We set $\phi = \vartheta = 0.03$ to generate a 6 percent spread between risk-free saving rates received by normal households and the risk-free borrowing rate.[23] Δ is set equal to 0.03; if one unit of model output is interpreted as $\$40,000$ – roughly median income in the US – then the filing cost is equal to \$1200.[24] Finally, $\xi = 0.25887$ implies that 95 percent of households who do not file for bankruptcy again will have clean credit after 10 years.

For λ, we employ a two-state Markov chain for the non-pecuniary cost of default with realizations $\{\lambda_1, \lambda_2\}$ and transition matrix

$$\Pi_\lambda = \begin{bmatrix} \pi & 1-\pi \\ 1-\pi & \pi \end{bmatrix}.$$

If $\pi > 0.5$, the underlying stigma cost is persistent; symmetry implies that the measure of households with each value of λ is 0.5.

We calibrate the parameters (β,λ_1,λ_2,β_s,π,α,δ) to match seven targets: a measure of borrowers equal to 12.5 percent, an aggregate negative net worth to GDP ratio of 1.41 percent, a bankruptcy

[21] In Athreya, Tam, and Young (2008) we study the effect of the rise in the volatility of labor income in the US and find it to be quantitatively unimportant. Therefore, we use the process estimated on the early data even though we compute the FI case assuming it applies to 2004.

[22] Recall that all special agents are college-educated types, so the total measure of college agents is 20 percent. We normalize units of measurement such that $N = 1$.

[23] The spread between saving rates and capital returns is thus equal to 3 percent, consistent with transactions costs measured by Evans and Schmalensee (1999).

[24] This cost is an estimate inclusive of filing fees, lawyer costs, and the value of time.

filing rate of 1.2 percent, a median discharge to median income ratio for filers of 56 percent, a risk-free saving rate of 1 percent, a 70 percent labor income share, and an annual depreciation rate of 10 percent. We identify debt with negative net worth in the model, an assumption that requires some defense. As noted above, in the data (as well as in the model), defaults are largely the province of the young (Sullivan, Warren, and Westbrook 2000); young households also have few gross assets, implying that negative net worth and unsecured debt largely coincide. Thus, our target captures the financial position of those households who are important for default empirically. The value for the ratio of negative net worth to GDP is taken from Sánchez (2008); we exclude the self-employed and consider both credit cards and installment loans as unsecured debt. For the measure of borrowers, we roughly average the numbers from Chatterjee *et al.* (2007) – 6.7 percent – and Wolff (2004) – 17.6 percent to get a ballpark measure of 12.5 percent.

Our target for bankruptcy is consistent with a model in which only income is uncertain; that is, there are no shocks to expenses. Expense shocks create involuntary creditors that allow households to suddenly acquire very large debts with no corresponding change in measured consumption. The difficulties in measuring rare "catastrophic" shocks, their true "uninsurability" (for example, Medicare and emergency rooms are always available to deal with medical shocks), and their persistence can lead to a serious mismeasurement of the role of credit use and bankruptcy for managing income risk. Furthermore, White (2007) casts some doubt on the evidence that such shocks contribute significantly to observed bankruptcy rates, and Sullivan, Warren, and Westbrook (2000) report that at most one-fifth of filers report that health played *some* role in their decision to file. We therefore calibrate the model's bankruptcy target to be net of this measure. Using an overall filing rate of 1.5 percent, our target becomes 1.2 percent. The median discharge to median income ratio that we use identifies negative net worth with discharged debt and is taken from Sullivan, Warren, and Westbrook (2000).

The resulting calibrated parameter values are listed in Table (1), along with all other parameters for the convenience of the reader. Special households are marginally more patient than normal ones; they hold almost 20 percent of total wealth based largely on their comparative advantage in savings returns. λ is fairly persistent – importantly, because households only borrow in the unsecured credit market for a relatively short period early in their life, their λ rarely changes over the relevant horizon. Highly-persistent λ values generate significant discharge in the model, and indicate the presence of highly persistent characteristics that implicitly collateralize borrowing. We discuss the role of λ more completely below.

4 Results

The first set of results we present concern our full-information benchmark. The section is divided into four subsections. The first two examine the equilibria under full and partial information, with particular attention devoted to the facts regarding debt, bankruptcy, and discharge. The third and fourth compute measures of consumption smoothing and welfare and compare them across information settings.

4.1 Full Information

In the full information case, lenders are assumed to observe the household's state vector, and thereby form forecasts of default risk that coincide with the borrowing household's own conditional expectation.

4.1.1 Aggregates

We first lay out the model's performance relative to the aggregate targets set for it and then discuss the role played some central model parameters related to default. Table (1) presents the aggregate unsecured credit market statistics from the model under full information. As seen from Table (1), the calibration procedure is quite successful; the benchmark model matches closely the targets we set in terms of the fraction of those with negative net worth, the overall level of unsecured debt, and the default rate. The ratio of median discharge to median income is smaller than the substantially broader measure in the data, which as discussed earlier includes both defaults driven by large expense shocks and the large debts associated with small-business failures (see Sullivan, Warren, and Westbrook 2000). As noted above, these shocks have only modest effects on filing rates, and we are able to target a default rate net of such considerations. Neither point holds with respect to discharge – defaults driven by either large expense shocks or small business failures are generally large and the data that separate discharge according to the reason for filing do not exist.[25]

The non-pecuniary cost of bankruptcy, λ, plays an important role in generating empirically-reasonable median discharge to median income ratios. It is meant to capture various aspects of deadweight costs borne by households in bankruptcy. There are two key aspects to this process – the coefficient of variation and the persistence. If one forces λ to remain constant and uniform across households when it is chosen to match the observed filing rate, the model produces a discharge-income ratio of only 5 percent and can no longer capture the heterogeneity in default costs implied by the estimates of Fay, Hurst, and White (1998). The calibrated value of λ in this case is also too small, in the sense that model generates counterfactually-small bankruptcies-and as a result will understate the welfare costs of frequent default. If λ differs across households but is iid, discharge rates remain too low as the average λ needs to be small. Without persistence, no household's implicit collateral is expected to be particularly valuable in the next period and thus cannot support large debts. Thus, our calibration allows for the high cross-sectional dispersion and high persistence in λ needed in order to jointly support (i) large risky debts on which default premia are paid (ii) frequent default, and (iii) relatively large discharges. If we change the average λ in the economy, the effect is to move default rates and discharge levels in opposite directions (see Athreya 2004). Furthermore, changing merely the average λ delivers little change in the dispersion in the terms. Thus, changes in stigma can also be dismissed as the force driving all of the changes in the unsecured credit market.

Lastly, we discuss the roles played by the two main transactions costs, Δ and ϕ. As noted in Livshits, MacGee, and Tertilt (2007) and Athreya (2004), dropping transactions costs can potentially deliver the trends in the default rates and debts observed in the data, so these changes are worth examining as competitor stories. No household in the model would default on any debt $b > -\Delta$, so higher values of Δ can support larger debts in general. Changes in Δ only alter the length of the initial flat segment where risk-free borrowing is sustained (Figure 7a plots price q as a function of pre-default borrowing b_{-1}). Changes in ϕ only shift the pricing functions up and down (see Figure 7b), altering the cost of issuing any given amount of debt. Thus, neither change will alter the variance of interest rates that agents receive, as they affect all agents symmetrically. To get a change in the distribution of interest rates, one needs to generate changes in the slope of the pricing functions. As a result, stories that place falling transactions costs at the heart of the changes in the unsecured credit market cannot account for the homogeneity observed in the earlier period. Usury ceilings in our model play almost no role – imposing a maximum interest rate of 25 percent does not alter the equilibrium in any quantitatively-important way.

[25] For example, Sullivan , Warren, and Westbrook (2000) mention bankruptcy cases in which among the personal assets of the filer are listed "specialized kitchen equipment", but such details are the exception, not the rule.

Having given a flavor of how pricing works in the model, we turn now to credit availability under full information; the 'supply side' of the credit market is seen most clearly in the pricing of debt facing households in varying states of income. For questions regarding unsecured credit, the young are the most relevant population, and we therefore focus on their access to credit. Figure (8a) displays the pricing functions for college types at age 29 given the low value of λ; as would be expected the higher the realization of e the more credit is available (at any given interest rate).[26] For low realizations of e the pricing functions look like credit lines – borrowing can occur at a fixed rate (in this case, the risk-free rate) up to some specified level of debt, after which the interest rate goes to ∞. For higher realizations the increase in the interest rate is more gradual, meaning that some risky borrowing will occur in equilibrium; for some borrowers, the marginal gain from issuing debt is sufficiently high that they are willing to pay a default premium to do it. The pricing functions for noncollege types look similar but involve higher interest rates at any given level of debt. Similar pictures arise for older agents – they are weakly decreasing in debt with more gradual increases in interest rates for luckier agents. Middle-aged agents (say, age 45) can borrow significantly more than their younger counterparts, although they choose not to do so in equilibrium because they are saving for retirement. For completeness, in Figure (8b) we plot the pricing functions for the high value of λ – as expected, these agents can borrow a lot more than low λ households can.

4.1.2 Distributions

Having documented the pricing that faces a variety of households in the model, we now report on the implication of these prices for observed borrowing on the equilibrium path. First, with respect to the distribution of unsecured debt, we show in Figure (9) that debts are incurred largely by college types – if they borrow, they borrow more than other groups. This larger borrowing reflects two aspects. First, college types have the most humped-shape average earnings profile. For purely intertemporal reasons they desire borrowing early in life in order to redistribute consumption. Given that the other two groups expect smaller rises in their average earnings over their lifetime, their intertemporal borrowing demand is much smaller. The second reason is that the credit market is simply more willing to permit college types to borrow, as shown in the pricing functions in Figure (8a-b) discussed above.

Figure (10) plots the life-cycle density of default for the model; consistent with empirical observations (Sullivan, Warren, and Westbrook 2000, Figure 2), default occurs mainly in the early periods of economic life because those are the periods in which agents are borrowing. Specifically, more than 70 percent of defaults are accounted for by households in which the primary petitioner is under the age of 45. In the model, default by the young is driven primarily by the hump-shape in average earnings; contrasting the non-high-school and college types shows clearly that large humps in average earnings generate a distribution of default skewed toward the young. If we remove the hump in earnings for the college type, we observe a very low and nearly-uniform distribution of defaults over the life cycle. The model predicts that filing rates are increasing in education, so that we overstate filings by college types and underpredict those for high school types.[27] These anomalies suggest that the nonpecuniary costs may covary positively with education.[28]

[26] The top panel plots the price functions for the lowest 5 realizations of e, the middle panel the middle 5, and the bottom panel the highest 5. ν is set to the mean value, since it plays only a limited role in the default decision.

[27] Linfield (2006) shows that college types constitute 24 percent of households and 15.5 percent of filers, while high school types are 56 percent of households and 78 percent of filers. Sullivan, Warren, and Westbrook (2000) argue that the distribution is roughly uniform over education groups, except for the group that reports "Some College" is overrepresented in filers (as of 1991).

[28] That interpretation would be consistent with stigma being a primary component of λ.

In addition to the age distribution of default rates, the model predicts that the largest defaults occur in middle age. Intuitively, defaults among the very young must involve relatively small debt levels; these households will choose not to borrow large amounts if they experience good earnings shocks, will not have had time to accumulate large debts if they have experienced moderate earnings shocks, and would not have been able to borrow large amounts had they experienced relatively bad earnings shocks. By contrast, by middle age purely intertemporal borrowing by those who had experienced mean earnings realizations will have had time to accumulate. Therefore, if such households experience poor earnings outcomes and choose to default, they will do so on relatively large amounts of debt.

A central issue in the analysis of bankruptcy is that of the role played by income shocks as "triggers." That is, how does income matter for the default decision? Figure (11) shows the default distribution over the income shocks.[29] First, those in default rarely, if ever, receive high realizations of the persistent shock. Very high e households do not default because they expect high future income and are therefore able to pay off debt without a large loss in consumption; thus, there is no reason for such households to pay any cost of default, particularly the nonpecuniary cost since it is (in consumption equivalents) larger for high consumption households. However, the converse of this is not true; low realizations of persistent income are rare among defaulters. Very low e households would default if they could manage to acquire debt; however, given the pricing functions in Figure (8), acquiring this debt is difficult; future income is flat and low so that borrowing will be followed by default under most circumstances. Because filers are generally younger households, the income level for those who go bankrupt is well below average, as in the data, even though they are not generally drawing the lowest shocks.

Transitory shocks matter as well; conditional on any given value for e, defaults occur most frequently among those with poor realizations of the transitory shock. Intuitively, transitory shocks, if large, can contribute substantially to observed default, because the current realization of a transitory shock is by definition useless for predicting default risk for any given level of debt even under full information. As a result, all households will face the price associated with the unconditional risk of bankruptcy; the credit market cannot "block" anyone from borrowing, as it would in the event of a bad persistent shock. In contrast, under the highly persistent shocks that are the empirically relevant case, those with poor shocks are unable to obtain debt in the amounts that generate significant default rates.[30]

Figure (11) also shows that the vast majority of defaults are done by low λ types. For high-cost types, persistent shocks matter for default only when transitory shocks are bad; the solid line shows a peak at low values of the persistent shock only in the left two panels of the figure. As a result, this group of defaulting households can be described roughly as those with permanent income similar to the average in the population, but who have suffered a temporary set-back to earnings. Those who face a high cost of default will not declare bankruptcy except under substantial hardship. However, the factors leading to current income being low must necessarily be transitory – otherwise creditors would have anticipated low-income, priced debt accordingly, and thereby reduced incentives to borrow. By contrast, for low-cost types the dashed line shows that the distributions of income are similar across realizations of the transitory shock.

[29] The presence of the very large spike in the central panel is due to the fact that the density for ν is $\{0.167, 0.667, 0.167\}$. The defaulters in the high ν panel are have recently switched from high to low λ, accounting for the absence of high ν, high λ defaulters.

[30] An economy with purely transitory shocks would likely have very high average interest rates in order to cover the losses from default.

4.1.3 Dispersion and Credit Sensitivity

A primary reason for our focus on improved information as a candidate explanation for the facts related to unsecured credit markets is the increase in dispersion of credit terms observed (and so paid in equilibrium). Figure (12) is a plot of the model's implications for the evolution of the variance of equilibrium borrowing rates over the life-cycle. Despite the strong age dependence of default rates, the dispersion in interest rates is fairly flat over the life-cycle, the variance is systematically higher for the higher educated groups, since those groups are the ones who borrow and default on the equilibrium path. In the model, agents are willing to pay fair premiums for the option to default and do so. Furthermore, since all pricing is actuarially-fair with respect to default risk, agents who pose higher risk will pay higher prices to borrow. Both observations are consistent with the relatively high dispersion and sensitivity found in recent data; we show below that the partial information setting will display neither characteristic.

Next, as documented in Edelberg (2006) and Furletti (2003), past default appears substantially more correlated with credit terms now than in past decades. In particular, the positive correlation of interest rates with past defaults may be seen as a form of "punitive" sanctions imposed by creditors. However, under competitive lending and full information, such penalties will not be viable. Nonetheless, given the persistence of shocks, the income events that trigger default may well persist, and therefore justify risk premia on lending. Indeed, we will show that this is a plausible interpretation of the data. Under full information, the credit market m reveals nothing about the household beyond what is contained in the rest of the state vector, but it is correlated with those states through the endogenous default decision. We partition the population $m = 0$ (no record of past bankruptcy) and $m = 1$ (a record of past bankruptcy) households. Table (2) displays the moments of agents conditional on having $m = 1$. Our model under full information predicts that credit scores will be correlated with credit terms – those who carry defaults on their record will pay more on average to borrow and borrow less.

In terms of a summary statistic of how much more sensitive credit terms are to past defaults, our model predicts an average "bad borrower" cost of 3 percentage points, very close to the differences in the modal interest rates across delinquent and nondelinquent households in Figure (3), though we probably overstate the borrowing of households after bankruptcy. Nonetheless, given that we do not target this moment in the data, our match of the premium on borrowing is additional evidence that changes in information lie at the heart of observed changes in unsecured credit markets. Crucially, we deliver this result without resorting to exclusion. Exclusion is *ex post* inefficient for lenders under full information, so it cannot be justified on theoretical grounds, and the data available only show that households borrow a lot less after bankruptcy, not whether they could not borrow or could and chose not to because of unfavorable terms.[31] Again, we will show below that the partial information setting will not have this property.

4.2 Partial Information

The central premise of our paper is that information held by creditors improved by enough to allow greatly increased risky lending. Having successfully calibrated the model to current observations under full information, we now ask our main question: Can a reduction of information lead the unsecured credit market to exhibit the features it has displayed throughout US history, until as recently as the early 1980's? Our results suggest that the answer is yes.

[31] Chatterjee *et al.* (2007) rely on the government to enforce exclusion through a moral suasion argument.

4.2.1 Aggregates

To remind the reader, partial information means that the lender is neither able to observe (a, e, ν, λ) nor total income. A central implication of our model is that partial information nearly eliminates the market for unsecured credit. At the level of credit aggregates, Table (3) shows our two central findings: both the default rate and unsecured borrowing declines precipitously – to nearly zero, in fact. Furthermore, the debt to income ratio for filers (discharge) is cut in half. Thus, the aggregates for the partial information equilibrium match closely those observed in the data prior to the 1980s.

Why does the credit market collapse in the economy with partial information? Consider our function q^0 above – that is, a pricing function that allows risk-free borrowing out to a level of debt that would generate default in every state of the world tomorrow; Chatterjee *et al.* (2007) refer to this level of debt as the endogenous borrowing constraint driven by a lack of commitment to repay. This pricing function cannot be an equilibrium, as high risk borrowers with debt near this level would default in at least some states of the world, creating a risk premium in lending. At the new higher interest rates low risk borrowers will borrow less, meaning that the high risk borrowers will now face even higher rates as their type is revealed. As a result, the high risk borrowers reduce their borrowing as well. This process, which is exactly the insight that we use to compute equilibria, apparently continues until the market reaches very low levels of debt and default – essentially, the bad risk types chase the good risk types all the way to zero. The thing that distinguishes good and bad credit risks in our model is the amount of borrowing they desire. Bad risk borrowers would like to borrow a lot, provided they can do so cheaply, and then default; the only way to get cheap credit is to pool with the good risk borrowers. But good risk borrowers are unwilling to pay high prices to borrow, so their borrowing falls. Our model suggests that the limited commitment that households have for debt repayment creates a very strong "lemons" effect.

Our main result is robust to changes in parameter values (such as the ratio of the variances of persistent and transitory shocks to income, the variance and persistence of the stigma shocks, the transactions costs for borrowing, and the risk aversion parameter) – better information always leads to more debt, more default, and more dispersion in terms. In no case is the size of the unsecured credit market significant. Crucially, our results are also robust to alternative assumptions about λ; in particular, we obtain the same results in a model with constant homogeneous stigma costs.

Our model succeeds quantitatively in greatly lowering credit use via adverse selection; however, to completely understand the mechanics of the model it is instructive to discuss the features that could sustain pooling at a high level of debt. That is, is a model such as ours is preordained to produce a strong lemons effect? Substantially weakening the lemons problem requires equilibrium homogeneity in the "value of default" across the agents who are pooled together; such homogeneity does not emerge in our model. Agents with good income prospects do not want to pay a premium to borrow, meaning that they are generally unwilling to remain pooled with households who value the default option highly.[32] This argument depends critically on persistence – if the unobserved characteristics are transitory, and therefore not useful for predicting future default, there is no distinction between "good" and "bad" borrowers and therefore no premium.

Adverse selection is made possible by the presence of unobservable "types". Unobservable types arise in our model from the presence of persistent factors relevant to default, namely, e and λ. The data strongly indicate the presence of a highly persistent component to household earnings; we have previously discussed why the calibration procedure generates high persistence in λ. As a result, those with differing realizations of e indeed constitute different types of agents in terms of

[32] As we have noted earlier, an environment in which total indebtedness is not observable displays more debt than the full information setting (based on very preliminary calculations).

the value they place on being able to issue defaultable debt. This heterogeneity ensures that those who place little value on default (e.g. those with high values of e) will not pay a premium to borrow. The preceding reasoning makes clear that when pooling is particularly disadvantageous to any one group, it cannot survive as an equilibrium. An immediate implication of this is that a setting with purely transitory private characteristics will not generate adverse selection at all. Because transitory private characteristics are not relevant for predicting behavior, they are not relevant for pricing. Though all individuals will be treated identically in this setting, and might well be able to borrow substantial amounts, such an outcome does not constitute a pooling equilibrium in which agents of genuinely different types face identical terms of credit.

Another question is how to generate additional separation in which some good risk borrowers do get systematically better terms under partial information. While plausible accounts of bankruptcy costs strongly indicate that they are lump-sum, proportional costs have the potential to generate separation. Specifically, if we assume that the pecuniary cost of default is proportional to the debt that will be discharged – that is, the filing cost is Δa – then high risk borrowers will expect to pay systematically higher costs relative to low risk borrowers for the same level of debt, leading potentially to separation between types. One can view this outcome as a policy prescription, although whether it improves welfare depends on whether the improved consumption smoothing for the good types outweighs the cost to the high risk types.

4.2.2 Distributions

Our model makes predictions for the distribution of the increased debt arising from a move from PI to FI. Specifically, we see that it is the college-educated whose behavior changes most in terms of both borrowing and bankruptcy: under FI, these households borrow most when young and default most frequently. In contrast, the equilibrium behavior of the non-college-educated changes very little in the move from PI to FI. These predictions of the model are both supported by recent work. Sánchez (2008) shows that distribution of unsecured debts, as measured by negative net worth, changed substantially between 1983 and 2004. Specifically, he shows that the bottom 30 percent of the earnings distributions saw its share of total debt *shrink*: the bottom decile held 24.9 percent of all unsecured debt in 1983 but just 10 percent in 2004, while the bottom quintile's share of debts fell by one-fourth (from 32.7 percent to 25 percent) over the same period. As a result, given the large absolute increase in unsecured debt levels, the data show that most of the new debt was acquired by households in the higher quantiles of the earnings distribution (who are mostly college-educated).

The intuition for the differential response across education levels to changes in information is as follows. Under PI, adverse selection limits borrowing by all groups, but this restriction on credit access affects the college-educated the most, as their mean age-earnings profiles contains the most pronounced hump across all education levels. Under FI, college-educated households' access to credit grows as adverse selection is mitigated, resulting in a large increase in indebtedness when young. In contrast, the nearly flat mean age-earnings profile for those without a high-school education makes them relatively less interested in borrowing under either PI or FI, except if they intend to default. Under either PI or FI, however, they will find themselves unable to borrow, but not for the same reasons. Under PI the strength of the adverse selection problem restricts their borrowing to only very small amounts, and under FI the pricing behavior of lenders causes their interest rates to rise precisely in those circumstances where they would want to borrow.

4.2.3 Dispersion and Credit Sensitivity

Quantitatively, the changes in both the measured dispersion in interest rates and the sensitivity of terms to bad credit indicators match extremely well with those in the data.[33] We stress that we made no attempt to calibrate the model to these changes, so they are an indication that improvements in information do indeed lie at the center of observed changes. Table (4) presents the model's predictions with respect to changes in the dispersion and sensitivity of credit terms. With respect to dispersion in credit terms, our main finding is that under PI every agent ends up borrowing at the same interest rate. Thus, dispersion falls sharply as information gets worse. Figure (13) shows the pricing function across different values of (e, ν, λ), compared to the ones obtained under full information. One clearly sees that all agents, not merely the low risk ones, are subjected to higher interest rates and lower effective credit limits under partial information. Almost all borrowing that does occur is done at the risk-free rate; since the low levels of debt observed in equilibrium are very close to the pecuniary filing cost Δ, it is almost never cost effective to exercise the option to default.

Turning next to the sensitivity of terms to individual credit history, notice that unlike the FI settings, changes in credit status m can reveal information about the borrower. However, how much information any such change contains, and in turn what effect it has on credit terms, depends endogenously on the strength of the adverse selection problem. Given the strong lemons problem our model displays, agents with $m = 0$ and $m = 1$ (under settings in which the PI model does have equilibrium default) end up borrowing at rates very similar to each other – both groups effectively borrow at the risk-free rate. Thus, the model under PI delivers credit terms that are insensitive to measures of credit worthiness, as documented by Edelberg (2006), Furletti (2003), and Livshits, MacGee, and Tertilt (2008). As noted above, alternative theories of rising default rates do not deliver increased dispersion of terms and increased sensitivity to individual circumstances.

The levels of both interest rates and dispersion measures are off in the model relative to the data. Specifically, as seen in Table (4) we underpredict the average interest rate in 1983 (PI) and overpredict it in 2004 (FI), leading to a change in $E(r)$ in the model that is in the opposite direction from that in the data. We note in our defense that transactions costs for lending are generally assumed to have fallen since the early 80s; if ϕ were higher in the PI setting then the average interest rate would also be higher. In addition, we have abstracted away from fixed costs; if lending contains a fixed cost component, ϕ_f, the pricing function must satisfy

$$q(b, I) = \frac{1 - \widehat{\pi}^b}{1 + r + \phi} - \frac{\phi_f}{b}, \tag{29}$$

then the decrease in the size of the average loan observed in the PI equilibrium would deliver endogenously a higher average interest rate. Furthermore, credit card rates are notoriously sticky in nominal terms (see Calem and Mester 1995) and this stickiness has been attributed to adverse selection (see Calem, Gordy, and Mester 2006). With respect to dispersion, the complete collapse of unsecured credit under PI ensures no cross-sectional dispersion in terms, rather than the small dispersion that would be observed in a PI setting that matched the small default rate observed in 1983. In summary, while we have abstracted away from the features needed to match the levels, the size of the changes in the unsecured credit market are precisely those predicted by an improvement in information.[34]

[33] We deflate interest rates in the data by the average expected interest rate from the Michigan Survey of Inflation Expectations over that year. In 1983, this number was 3.4 percent and in 2004 it was 3.0 percent.

[34] Imperfect competition in the early period is a possible force that would raise average interest rates. However, our information story would still be present even if the market power of lenders declined over time, since a market

4.3 Consumption Smoothing

We now turn to some of the consequences of improved information for consumption. In Figure (14) we plot the mean of log consumption over the life-cycle under the two assumptions about information. Mean consumption is lower under full information than partial information due to the transactions costs of borrowing ϕ and defaulting Δ, particularly for older households. When agents borrow and default more, they destroy more resources and leave themselves less wealth to finance lifetime consumption (since the risk-free rate and wage rate are basically unchanged, the present value of lifetime earnings is not affected to any significant degree). One can thus interpret ϕ and Δ as insurance premia paid for the right to borrow and introduce limited state-contingency into returns. Under FI, transactions costs destroy 9.34 percent of output, while under PI, this number falls to 8.88 percent; in contrast, under NBK, transactions costs destroy 9.82 percent of output as there is significantly more borrowing.

Turning to consumption volatility, we find it helpful to decompose volatility into two components:

$$V(\log(c)) = E[V(\log(c)|j)] + V(E[\log(c)|j]); \tag{30}$$

the total variance of log consumption $V(\log(c))$ is the mean of the variances of log consumption conditional on being age j plus the variance of mean log consumption conditional on being age j. The first term yields a measure of *intratemporal* smoothing – it is the average dispersion of consumption occurring within households of any given age and so provides a natural measure of "risk sharing". The second term measures *intertemporal* smoothing by capturing the extent to which mean consumption – which is precisely what would obtain for *all* households under complete insurance markets – evolves over the life-cycle. In Table (5) we present the aggregates for these two measures.

The variance of consumption is high early in the life-cycle because households are restricted in their ability to borrow when young, inhibiting consumption smoothing. Consumption smoothing becomes less effective for most ages under partial information because borrowing is essentially impossible; thus, the young in particular experience significant consumption fluctuations.[35] However, households that borrow early in life must repay debts as they age, leaving them exposed to income risk later in life. Because the partial information economy does not permit borrowing, these older households are able to smooth their consumption effectively using buffer stocks of savings accumulated earlier in life; of course, the fact that they can smooth their consumption effectively when old does not mean that they are better off *ex ante*.

This result makes clear that the tradeoff discussed in Livshits, MacGee, and Tertilt (2007) based on aggregates alone may not be a general one – in our setting, bankruptcy does not necessarily improve the ability to smooth consumption across states of the world at the expense of smoothing over time.[36] Instead, it improves smoothing for some households – older ones – at the expense of younger households who cannot borrow. It also suggests that evaluating the costs of bankruptcy reform may require more general preferences that permit disentangling risk aversion from the elasticity of intertemporal substitution in consumption; we are planning a companion paper in which we extend our model to households with the preferences developed in Epstein and Zin (1989).[37]

power story would fail to deliver increased dispersion in terms. Ausubel (1991) contains a discussion of the structure of the industry.

[35]See Athreya (2008) for more details.

[36]In Athreya, Tam, and Young (2008) we provide two-period examples in which bankruptcy can inhibit or improve intertemporal smoothing and inhibit or not affect intratemporal smoothing. We find that the expected value and expected variance of income tomorrow are critical for determining whether default helps or harms consumption smoothing.

[37]Nakajima (2008) considers the welfare implications of bankruptcy reform in a model with temptation preferences

4.4 Welfare

We conclude this section of the paper with two simple welfare calculations: How valuable was the gain in information and how does this number compare to the gain from eliminating the default option? In Table (6), the consumption equivalent C_{eq} is the percentage that consumption must be increased in each period to make newborn households indifferent between two economies, conditional on the newborn observing their permanent shock y.[38] The model suggests that the welfare costs of adverse selection can be significant – these costs are orders of magnitude larger than the welfare cost of business cycles, for example, even in models with incomplete markets (Krusell and Smith 2002). It is important to stress that these calculations are not the welfare gains generated by a change in policy; that calculation would require computing the transitional dynamics between steady state distributions. Given that there are only very weak general equilibrium effects at play (other than the individual pricing functions), we do not think that paying the costs of computing a transition are worth it; fortunately, the same consideration suggest that our welfare calculations will not be too inaccurate.

All newborn households are better off under full information – because the model does not feature any cross-subsidization under partial information, there is no type that suffers when information is revealed. But college types benefit much more than the other types, largely due to their desire to borrow against the much-higher income they expect later in life. Since adverse selection completely disrupts borrowing, these types gain quite a lot. It also explains why college types gain even more from the elimination of bankruptcy, since that setting permits borrowing out to the natural debt limit. Our numbers in this section, when combined with those in Table (5), show that consumption variance is a misleading indicator of welfare. While the intertemporal measure gets the right welfare ranking, the intratemporal measure does not – partial information would appear to generate the highest welfare. Thus, one needs to be careful when extrapolating from measurements of consumption volatility to measurements of welfare.[39]

Welfare gains from eliminating bankruptcy are larger when bankruptcy rates are low (partial information), because the gains of bankruptcy elimination include the gains from better information – in fact, the welfare gains are essentially additive, suggesting that there are only small complementarities between information improvements and bankruptcy elimination. If bankruptcy is not an option, the information problem disappears: if a borrower cannot discharge debts, the lender does not need to assess default risk and therefore does not bother forming beliefs over the borrower's states. This result has an interesting interpretation – society can solve this particular asymmetric information problem by solving the limited commitment problem created by bankruptcy instead. One lesson that we take from this observation is that policymakers should not attempt to reverse the recent increase in default rates; rather than reflecting the bad faith attempts by borrowers to rid themselves of debt they should not have been able to take on in the first place, high default rates reflect the fairly-priced gambles taken by young households in an attempt to shield themselves from bad shocks early in the life-cycle.[40]

(Gul and Pesendorfer 2001). He discusses whether the welfare implications of bankruptcy reform depend critically on self-control problems faced by households.

[38] The welfare cost before observing y would just be the weighted average of the costs for the different types.

[39] We are not the first to note this point; Krueger and Perri (2004) contains a long discussion of the welfare changes that rising income volatility has caused.

[40] There is a large law and economics literature on the welfare implications of bankruptcy options; Porter and Thorne (2006) is one example with many references for the interested reader. That literature argues that bankruptcy has positive welfare implications precisely because it conflates current economic conditions with utility.

5 Concluding Remarks

In this paper, we have shown that improved information held by unsecured creditors on factors relevant for the prediction of default can account for, in a unified way, many of the changes seen in unsecured credit markets. We find that five big trends in unsecured credit markets – rising debt, rising default, rising discharge, increasing dispersion of interest rates, and increasing good borrower discounts – are all consistent with an improvement in the ability of the market to observe characteristics about borrowers. Our model also has a clear welfare implication – more information in the unsecured credit market is better for *all* types – which, among other things, strongly suggests that the recent increase in bankruptcies is not something that policymakers should attempt to reverse.

A technical contribution of our work is an algorithm to compute equilibria with individualized pricing and asymmetric information. In two companion papers we make use of our model and algorithm to study two questions. First, we are studying how regulatory conditions that constrain information in the credit market affect the economy; for example, the Equal Credit Opportunity Act explicitly bans the use of age, race, and gender for the determination of credit. Such bans may serve noneconomic goals, but they may also impose costs on the economy by pooling different types of borrowers together.[41] Second, in Athreya, Tam, and Young (2008) we ask how the dramatic increase in labor income risk impacted the use and efficiency of the unsecured credit market; as the title of that paper suggests, our key finding is that unsecured credit markets cannot function as insurance markets no matter which information regime prevails.[42]

A feature of recent work on consumer default, including the present paper, is that it imposes a type of debt product that may not mimic all the features of a standard unsecured contract offered by real-world credit markets. In our model individuals issue one-period bonds in the credit market. As a result, any bad outcome is immediately reflected in the terms of credit, making consumption smoothing in response to bad shocks difficult (credit tightens exactly during the period in which it is most needed); this arrangement would seem to artificially increase the incentive for default.[43] In our defense, credit contracts explicitly permit repricing by the lender at will, but an open question regards the extent to which they use this option.[44] Given that credit conditions are typically only adjusted by two events – default or entering the market to either purchase more credit or to retire existing lines – credit lines may be a more appropriate abstraction. Whether it makes a significant difference for consumption smoothing is the subject of future work.[45]

[41]Inference in a model with regulatory constraints is subject to more restrictions than those discussed here. Intermediaries want to form beliefs about the unobserved characteristics of borrowers, but if those inferences prove too accurate they can be fined by the regulator; that is, if the equilibrium reveals that a banned characteristic is informative about credit terms the intermediary is subject to penalties, even if the characteristic is not explicitly used, limiting the value of the sophisticated inference procedure considered here.

[42]Empirical support for the changing variance of shocks can be found in Gottschalk and Moffitt (1994), among others. See Athreya, Tam, and Young (2008) for more references.

[43]We discuss this point in detail in Athreya, Tam, and Young (2008), as it forms the basis of our argument that credit markets cannot provide effective insurance against increased income risk.

[44]In an interview with Frontline in 2004, Edward Yingling, at the time the incoming president of the American Bankers Association, notes that

> the contract with the credit card company is that "We have a line of credit with you, but we do have the right at any time to say we're not going to extend that credit to you anymore," which, by the way, also includes, "We have the alternative to say you are now a riskier customer than we had when we opened the agreement; we have the right to increase the interest rate, because you now have become a riskier customer."

Thus, credit card companies do appear to use this option on occasion.

[45]Mateos-Planas (2007) is a recent attempt to model credit lines with homogeneous interest rates and lender

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Table 1: Parameters/Calibration

Parameters				
$\sigma = 2.0000$	$\vartheta = 0.0300$	$\Delta = 0.0300$	$\lambda_2 = 0.0358$	$\Theta = 0.2000$
$\beta = 0.9823$	$\beta_s = 1.0024$	$\xi = 0.2589$	$\pi_{HH} = \pi_{LL} = 0.8668$	$\alpha = 0.3000$
$\phi = 0.0300$	$\mu_s = 0.0500$	$\lambda_1 = 1.6715$	$\theta = 0.3500$	$\delta = 0.1000$

Calibration	Model	Target
Discharge/Income Ratio	0.2760	0.5600
Fraction of Borrowers	0.1259	0.1250
Debt/GDP Ratio	0.0208	0.0141
Default Rate	1.366%	1.200%

Parameters defined in text.

Table 2: Credit Sensitivity

	$b < 0, m = 0$		$b < 0, m = 1$	
Mean	b	q	b	q
$Coll$	0.2769	0.9038	0.1243	0.8703
HS	0.0842	0.8490	0.0440	0.8233
NHS	0.0332	0.8034	0.0278	0.7306

Table 3: Unsecured Credit Market Aggregates

	FI	PI
Discharge/Income Ratio	0.2760	0.1379
Fraction of Borrowers	0.1259	0.0479
Debt/GDP Ratio	0.0208	0.0011
Default Rate	1.366%	10^{-4}%

Table 4: Dispersion and Credit Sensitivity

	1983		2004	
Levels	Data	Model	Data	Model
$E(r)$	14.72	4.00	9.85	14.96
$E(r\|m=1)$	14.50	4.00	11.63	15.85
$E(r\|m=0)$	14.72	4.00	9.46	13.60
$Var(r)$	7.90	0.00	26.63	18.85
$Var(r\|m=1)$	8.68	0.00	33.88	25.33
$Var(r\|m=0)$	7.53	0.00	25.60	17.84
Changes	Data	Model	Data	Model
$E(r\|1983)$-$E(r\|2004)$			5.67	-10.96
$E(r\|m=1)$-$E(r\|m=0)$	-0.22	0.00	2.23	2.25
$Var(r\|m=1)$-$Var(r\|m=0)$	1.15	0.00	7.28	7.59
$Var(r\|1983)$-$Var(r\|2004)$			18.73	18.85
$Var(r\|m=1,1983)$-$Var(r\|m=1,2004)$			25.20	25.33
$Var(r\|m=0,1983)$-$Var(r\|m=0,2004)$			18.07	17.84

Table 5: Consumption Smoothing

	FI			PI		
	Coll	HS	NHS	Coll	HS	NHS
Intra	0.1134	0.1539	0.2112	0.1005	0.1518	0.2120
Inter	0.0260	0.0220	0.0221	0.0306	0.0243	0.0232
Total	0.1394	0.1759	0.2333	0.1311	0.1761	0.2352

Intra measures the variance of (log) consumption across households of any given age.
Inter measures the variance of mean (log) consumption over the lifecycle.
See Equation (30) for detail.

Table 6: Change in Welfare

	Coll	HS	NHS
$PI \to FI$	0.86%	0.32%	0.13%
$FI \to NBK$	2.64%	1.18%	1.06%
$PI \to NBK$	3.50%	1.50%	1.19%

Figure 1: Chapter 7 Bankruptcy Filings per Household

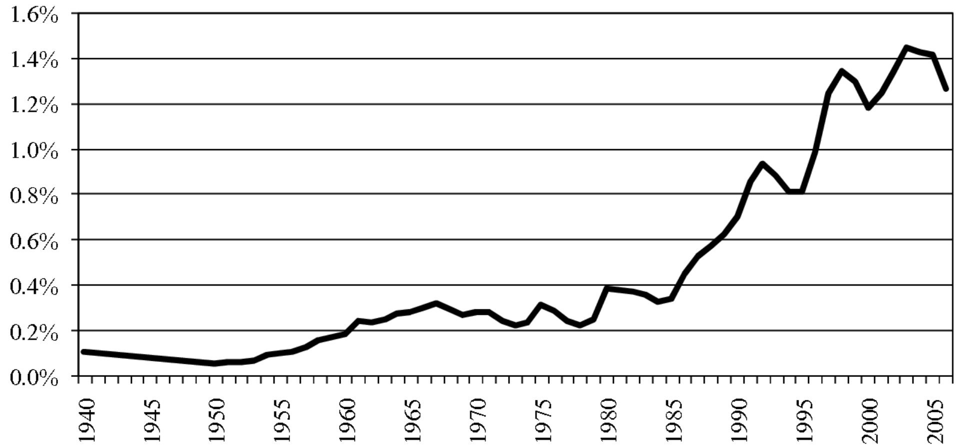


Figure 2: Income and Debts of Bankruptcy Filers

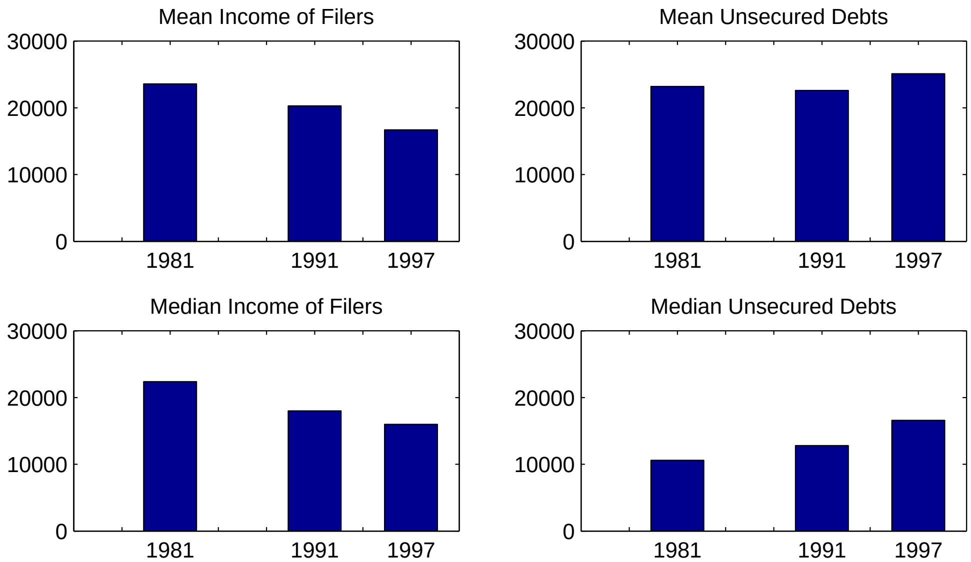


Figure 3: Distribution of Interest Rates on Positive Credit Card Balances

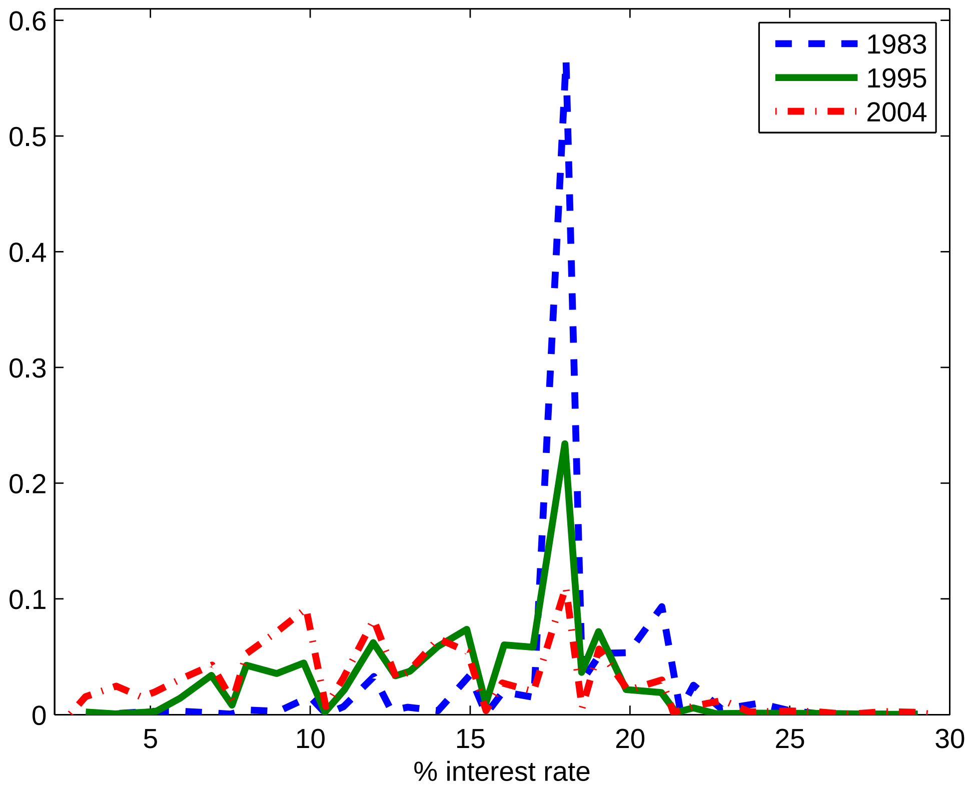


Figure 4: Delinquent and Nondelinquent Borrowers

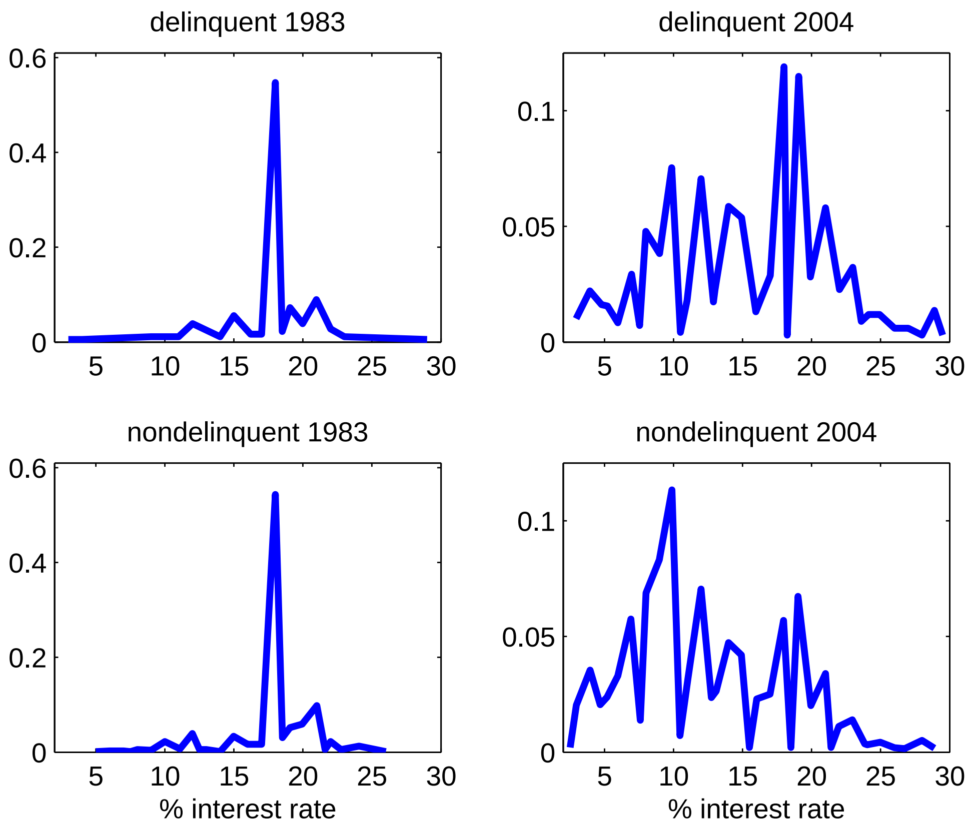


Figure 5: Inference Problem

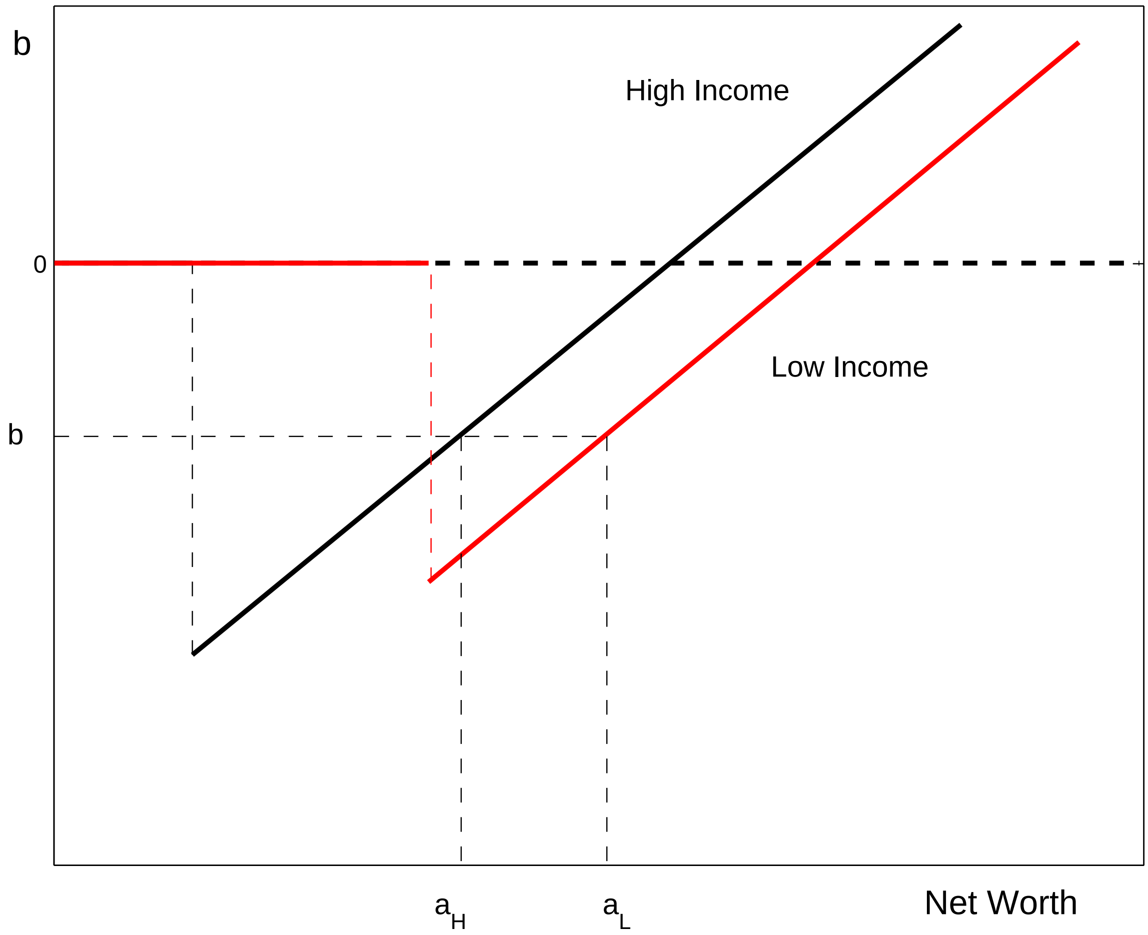


Figure 6: Labor Productivity over the Life-cycle

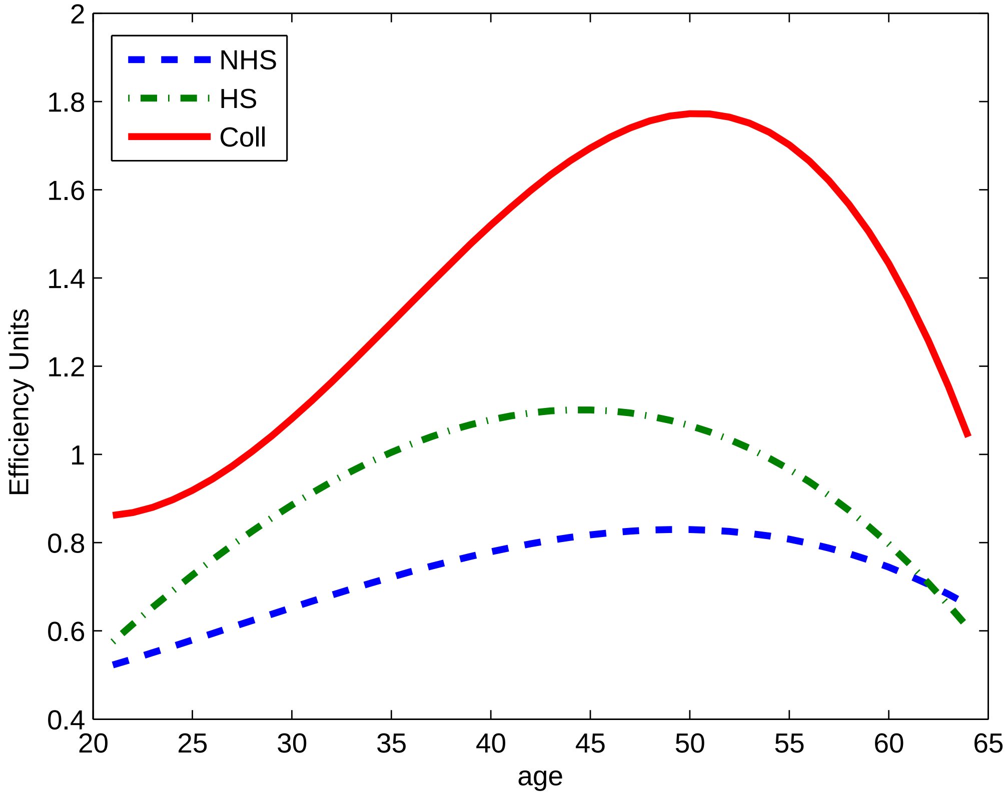
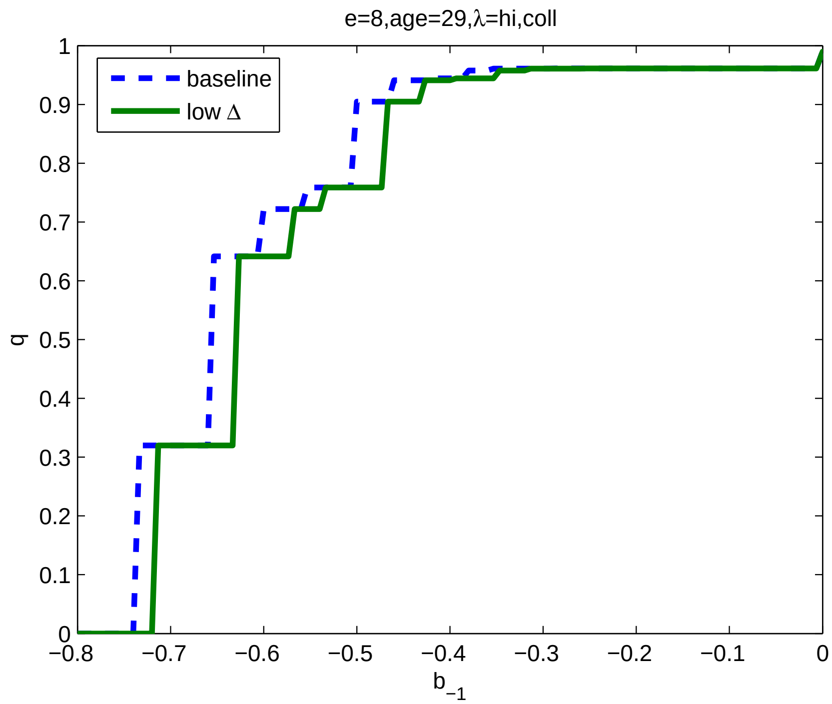
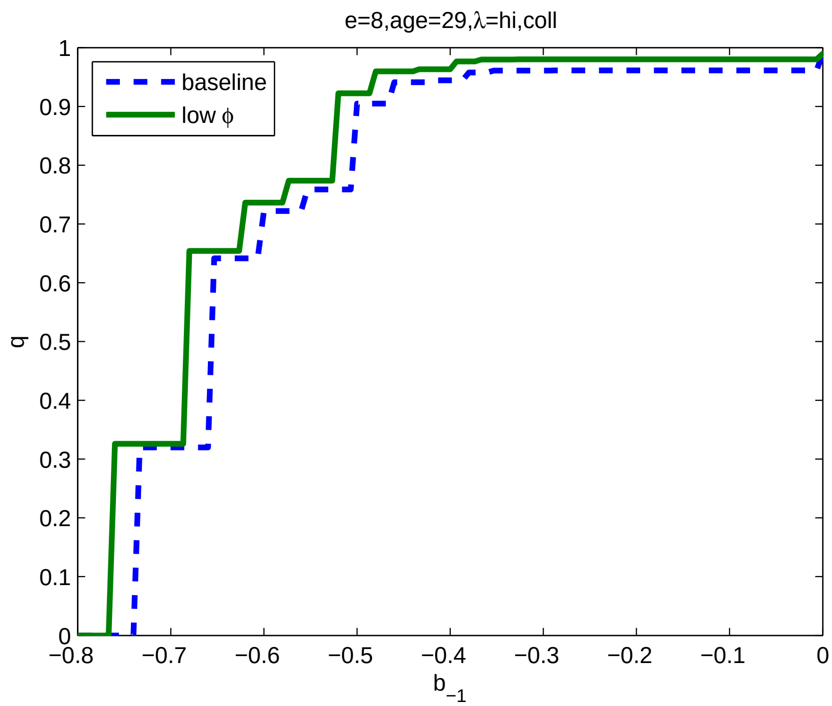


Figure 7: The Role of Transactions Costs

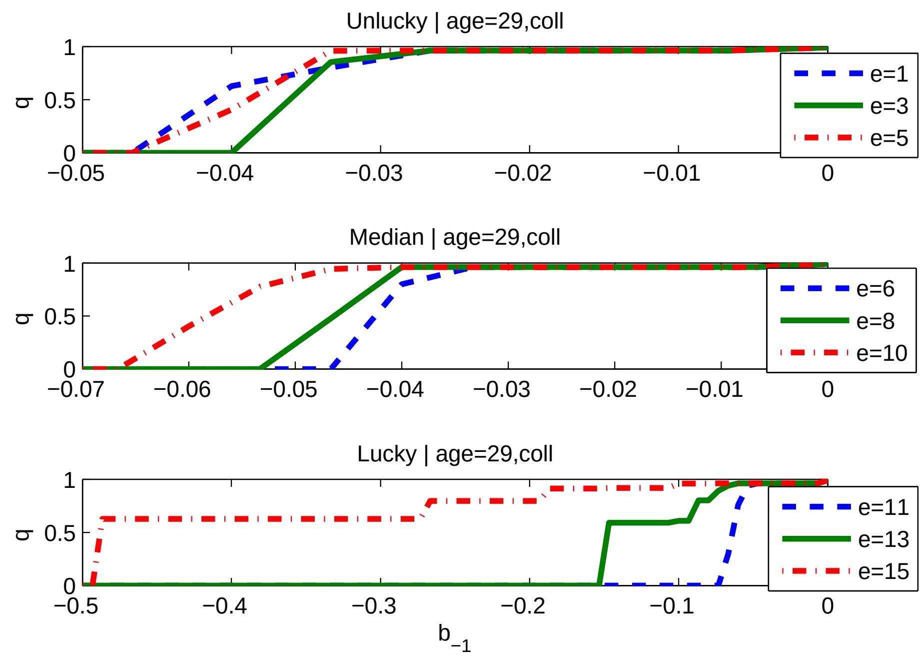


(a) Low Δ

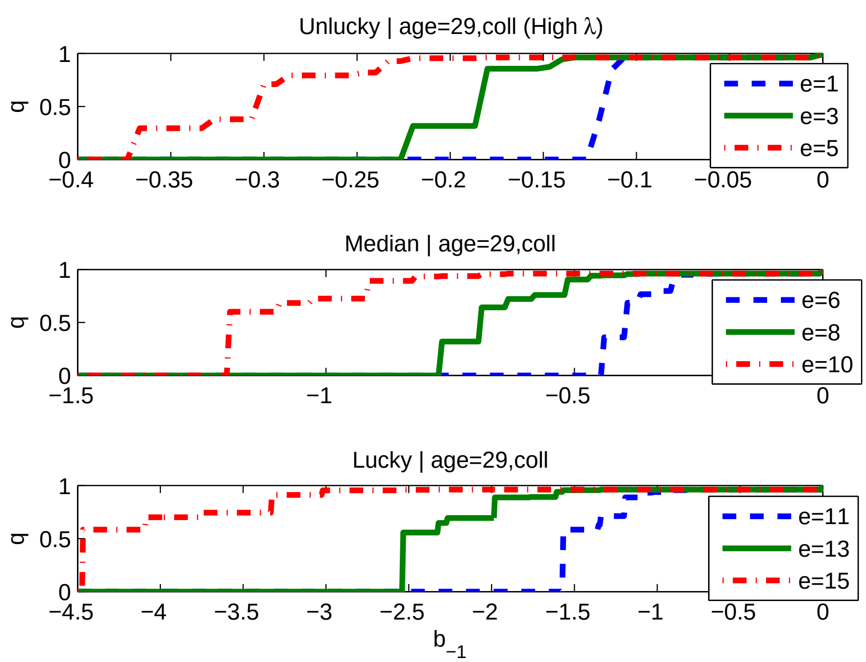


(b) Low ϕ

Figure 8: Price Functions



(a) Low λ



(b) High λ

Figure 9: Mean Debts over the Life-Cycle

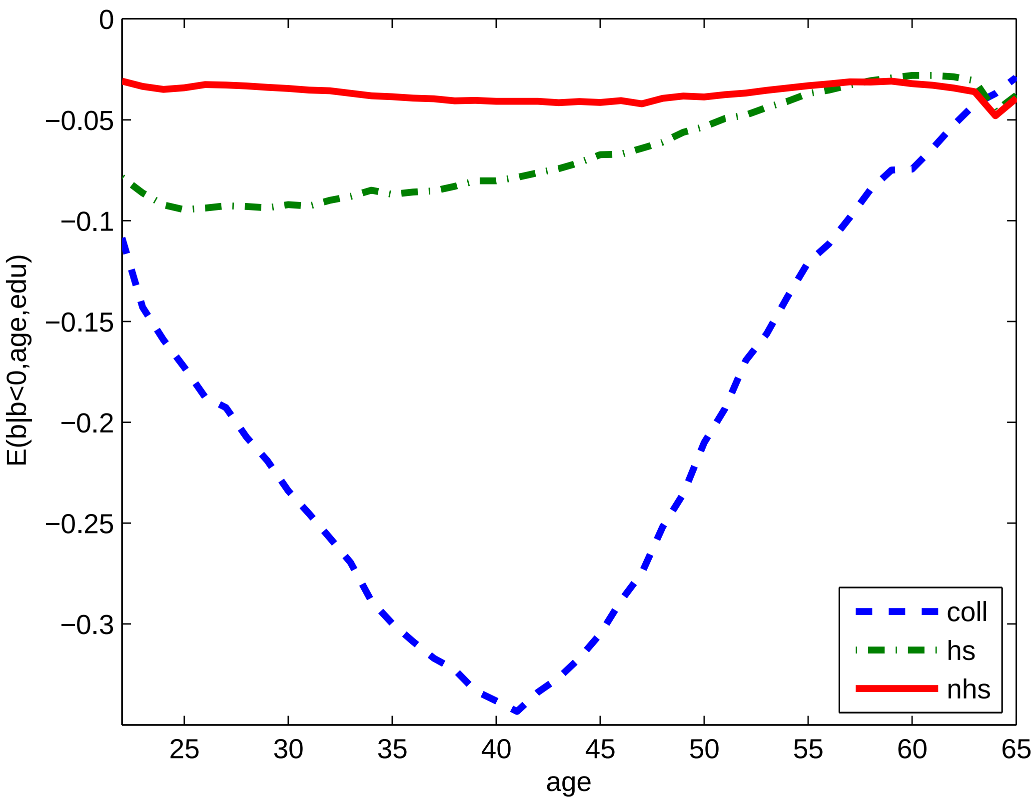


Figure 10: The Age Distribution of Defaulters

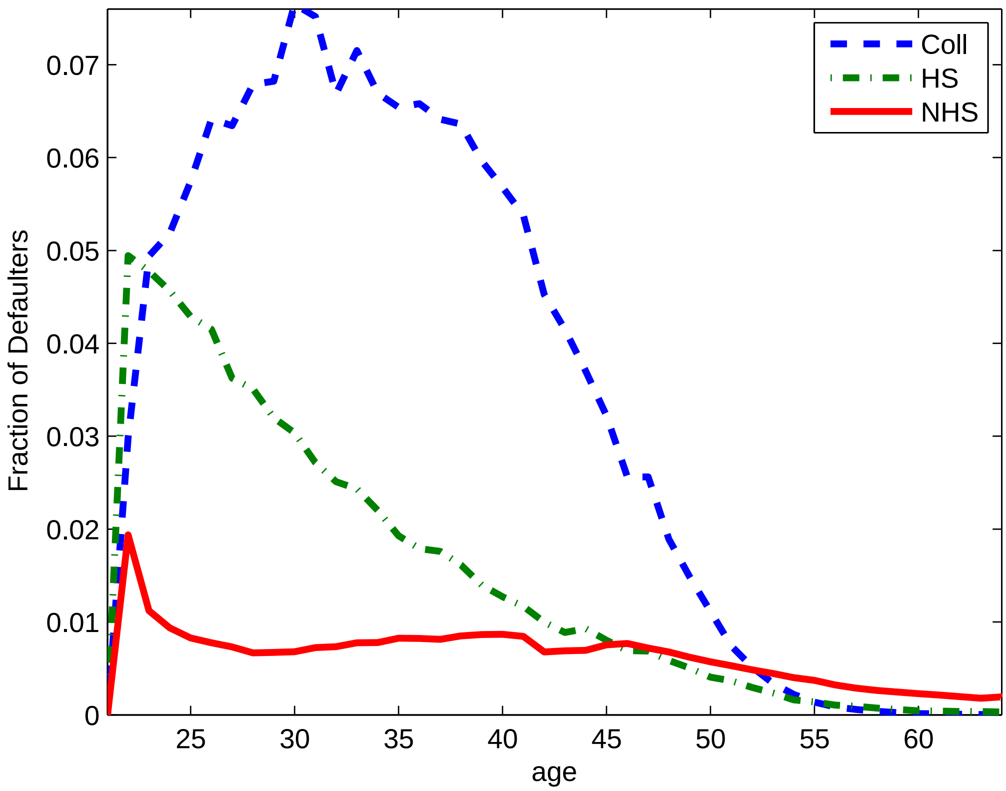


Figure 11: The Income Shocks of Defaulters

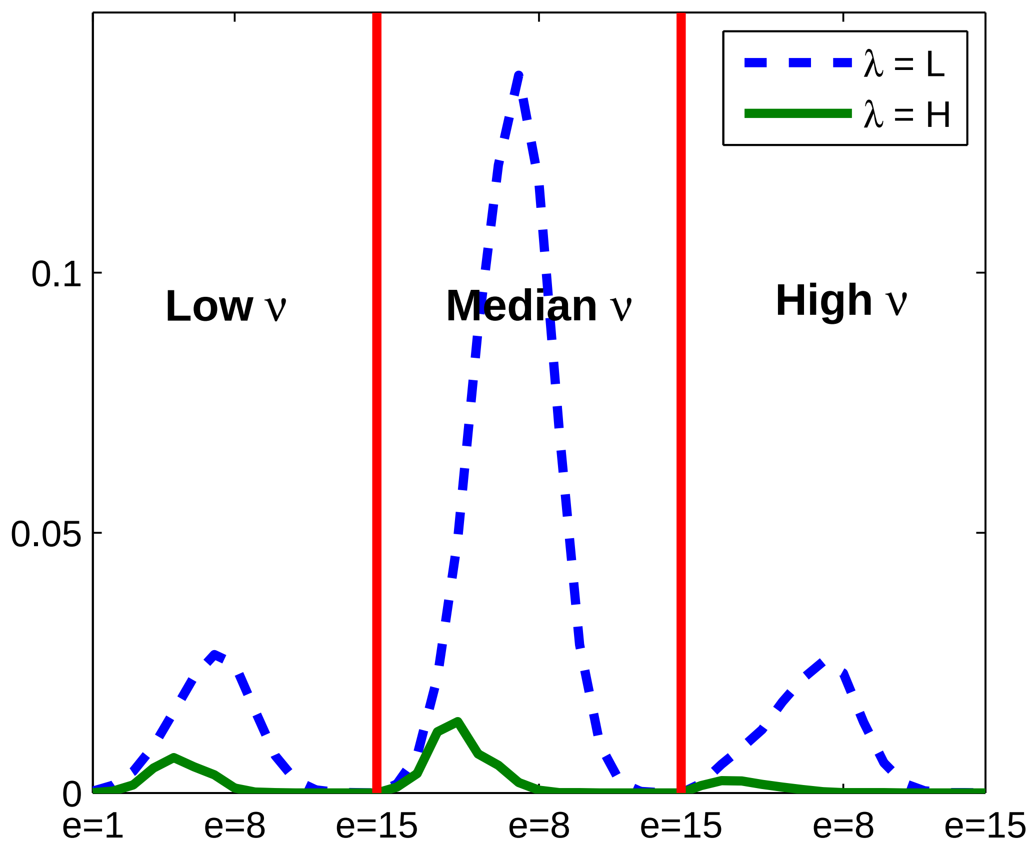


Figure 12: Variance of Equilibrium Borrowing Rates over the Life-Cycle

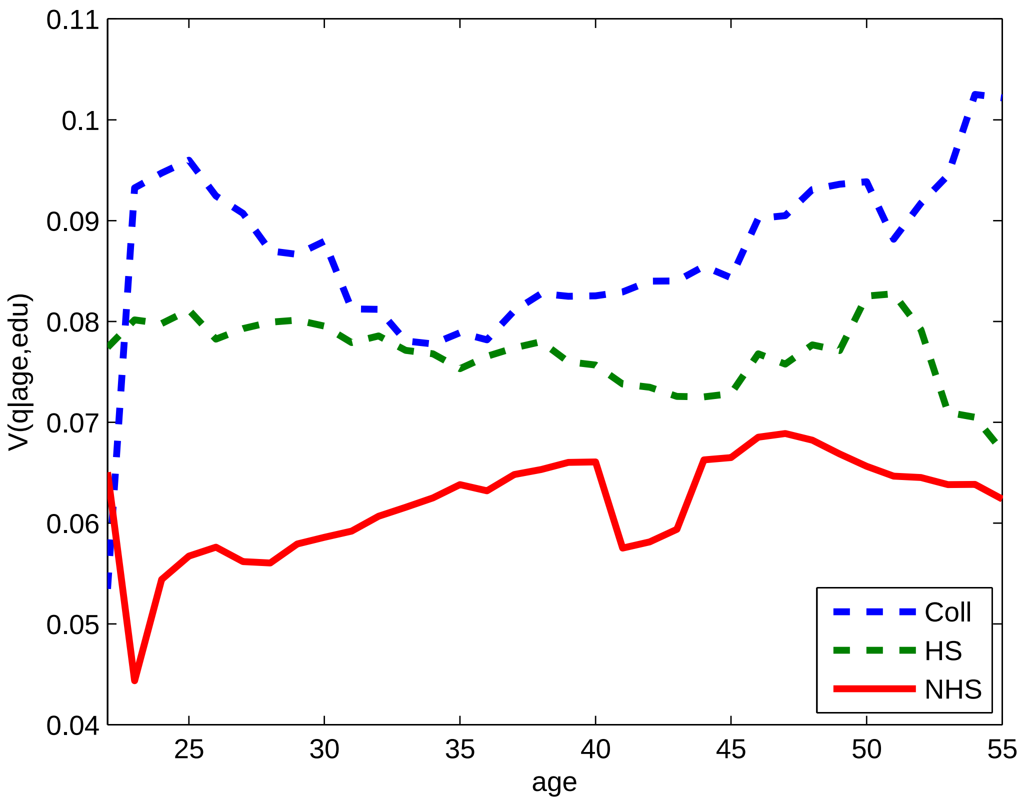


Figure 13: Information and Loan Pricing

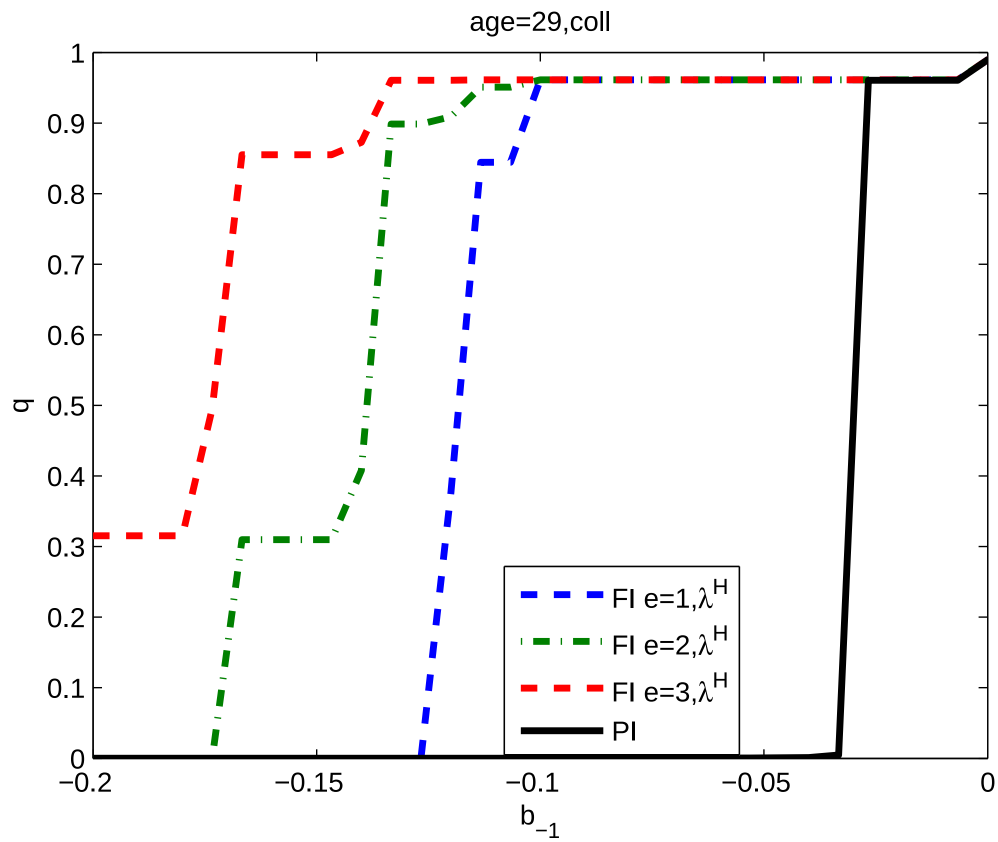


Figure 14: Information and Consumption over the Life-Cycle