Employer Credit Checks:
Poverty Traps versus Matching Efficiency

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Abstract

We develop a framework to understand pre-employment credit screening as a signal from credit markets that alleviates adverse selection in labor markets. In our theory, people differ in both their propensity to default on debt and the profits they create for firms that employ them; in our calibrated economy, highly productive workers have a low default probability. This leads firms to create more jobs for those with good credit, which creates a poverty trap: an unemployed worker with poor credit has a low job finding rate, but cannot improve her credit without a job. This manifests as an endogenous loss in present-discounted wages that is typically taken as exogenous in quantitative models of consumer default. Banning employer credit checks eliminates the poverty trap, but pools job seekers and reduces matching efficiency: average unemployment duration rises by 2 days for high productivity workers and falls by 13 days for low-productivity workers.

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"We want people who have bad credit to get good jobs. Then they are able to pay their bills, and get the bad credit report removed from their records. Unfortunately, the overuse of credit reports takes you down when you are down." Michael Barrett (State Senator, D-Lexington, MA).

1 Introduction

The three largest consumer credit agencies (Equifax Persona, Experian Employment Insight, and TransUnion PEER) market credit reports to employers, which include credit histories and public records (such as bankruptcy, liens and judgments). According to a Survey by the Society for Human Resource Management (2010), 60% of human resource representatives who were interviewed in 2009 indicated that their companies checked the credit of potential employees. Furthermore, a report by the policy think tank DEMOS found that 1 in 7 job applicants with bad credit had been denied employment because of their credit history (Traub [45]).

Until recently, pre-employment credit screening (PECS) was largely unregulated and remains so at the federal level – the FTC writes "As an employer, you may use consumer reports when you hire new employees and when you evaluate employees for promotion, reassignment, and retention as long as you comply with the Fair Credit Reporting Act (FCRA)."[1] However, since 2005, numerous state and federal laws have been introduced with the goal of limiting or banning employer credit checks and, as of 2018, eleven states have enacted such laws.[2] Legislators often express concern of a "poverty trap" arising due to employer credit checks: a worker cannot improve her credit report without a job, but bad credit makes it harder for her to find a job in order to improve her credit. We build a model of unsecured credit and labor market search with adverse selection in which such poverty traps arise endogenously, which we use to assess the welfare consequences of policies to ban PECS.

A growing empirical literature seeks to estimate the effects of PECS on labor market outcomes. Most directly related to this paper, Cortes et. al. [14] estimate a fall in posted vacancies for affected occupations following the implementation of employer credit check bans, but not in occupations that are exempted (jobs with access to financial or personal information). We reproduce Figure 1 from their paper in Figure 1a. This plot shows the difference between vacancies posted by employers in occupations who are forbidden from using credit checks relative to occupations that are exempt in employer credit check bans (which means they retain the ability to check the credit reports of job applicants). Figure 1a shows that vacancies in affected and exempt occupations follow a similar path before a ban goes into effect (since the difference is approximately zero on average before the ban goes into effect at $t = 0$) while affected occupations experience a significant decline in posted vacancies following the ban, which persists

[1] http://www.ftc.gov/bcp/edu/pubs/business/credit/bus08.shtm

[2] The states with bans are CA, CO, CT, DE, HI, IL, MD, NV, OR, VT, WA.

even after a year.[3] Their labor market estimates are directly related to the labor demand effect of our theory.

An additional feature of our theory that has not yet been studied empirically is the effect of employer credit check bans on consumer credit markets. Specifically, in our model, consumers are incentivized to repay debts by the effect of their future credit score on their job finding rate and expected earnings. Therefore, banning the use of credit checks by employers removes an incentive to repay and increases the rate of strategic default. Importantly, our model predicts that people with higher credit scores are the most affected by this reduction in dynamic repayment incentives, since they are more patient on average and are therefore more responsive to future labor market outcomes than people with low scores.

Figure 1b provides support for this mechanism by plotting regression coefficients of a linear probability model that projects an indicator that the borrower has a delinquent account on state-level employer credit check bans interacted with borrower-level Equifax Risk Scores using the NYFed/Equifax Consumer Credit Panel.[4] While our model equivalent of a credit score is not directly equivalent to the Equifax Risk Score, we use it as a proxy. The positive coefficients after a ban goes into effect indicate an increase in delinquencies for consumers with higher Equifax Risk Scores. Pooling the post-ban estimates, we find that consumers who are one standard deviation above the mean Equifax Risk Score are 1.1 percentage points more likely to become delinquent after employers are restricted from using credit reports in the hiring process.[5] This is consistent with our model, where people with good scores are more sensitive to the future costs of a current default, such as worse labor market outcomes.

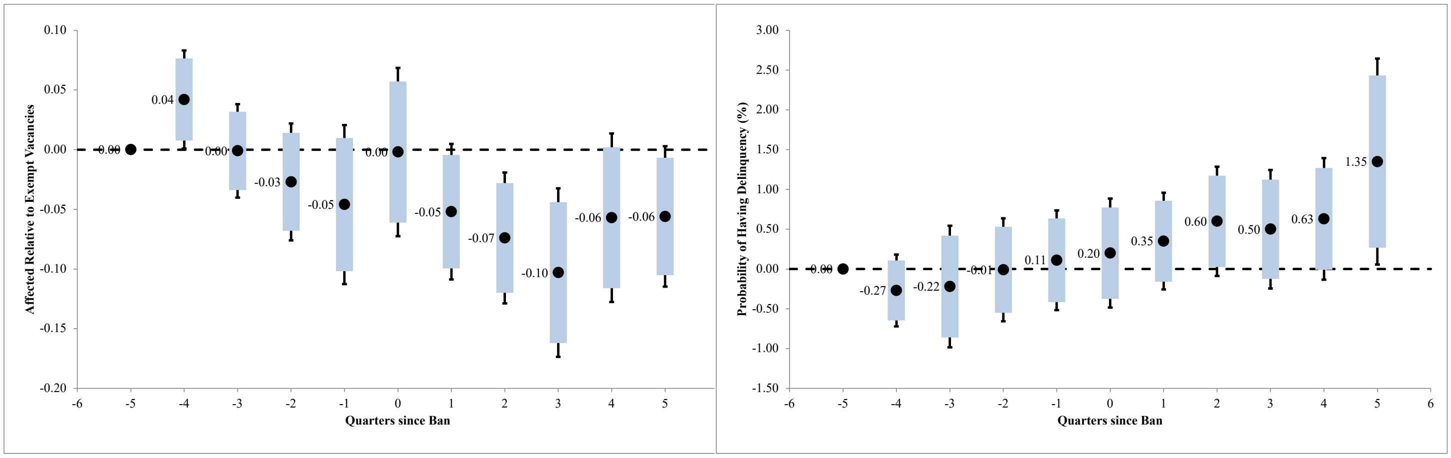
Motivated by the above empirical work on PECS, we develop a quantitative dynamic equilibrium model in order to understand the positive and normative implications of PECS. Our model features three key components: an unobservable characteristic that we model through heterogeneous time preferences (which creates adverse selection in both default probabilities and productivity through an endogenous effort choice), labor search frictions, and unsecured credit with endogenous default. Employers value the PECS process because credit records are an externally verifiable and inexpensive signal about a *residual* component of labor productivity that is not observable *before* the worker is hired.[6] We infer that worker types with high patience also have high residual labor productivity from the negative cross-sectional correlation between credit delinquency and residual earnings. We model the underlying correlation be-

[3]The difference between affected and exempt post ban is -5.5% and is statistically significant at the 5% level.

[4]The CCP is a nationally representative anonymous random sample from Equifax credit files that tracks the credit use and address of approximately 12 million individuals at a quarterly frequency. See Appendix F for a description of the data and regression results associated with Figure 1b.

[5]This estimate is significant at the 5% level with standard error clustered by state and time.

[6]In our model, a credit record contains the borrower's history of debt repayment. This will map into a worker's ex-ante probability of being a high-patience/productivity type, which coincides with a higher ex-ante probability of repaying debt. We will therefore refer to the worker's "score" rather than report, since it is this probability of being high-patience/productivity that is relevant for employers and lenders.



(a) (b)

Notes: Regression for vacancies is reproduced from Cortes et. al. [14]. Vacancies are classified by $o \in \{exempt, affected\}$. The estimated equation is

$$\log \text{vacancies}_{c,o,t} = \sum_{k=-4}^{5} \beta_k^o \text{Affected}_{o,c} \times \text{BAN}_{c,t-k} + \text{FE}_{c,t} + \text{FE}_{o,t} + \varepsilon_{c,o,t},$$

where $BAN_{c,o,t} = 1$ if county c has a PECS ban in quarter t and occupation o is affected. Lead-lags are in quarters, with -5 representing one year before the ban (normalized to zero) and 5 representing more than one year post ban. Blue boxes are 90% confidence intervals. Exempt occupations are two-digit SOC codes representing Business and Financial (SOC-13), Legal (SOC-23), and Protective Services (SOC-33).
Regression for delinquencies uses the NYFed/Equifax Consumer Credit Panel to estimate the differential change in delinquent status of individual consumers as an employer credit check ban is implemented. The estimated equation is

$$\text{D}_{i,s,t} = \beta_p \text{BAN}_{s,t} \times RiskScore_{i,t} + \sum_{k=-4}^{5} \beta_k^o \text{BAN}_{s,t,k} \times \text{RiskScore}_{i,t} + \gamma \text{RiskScore}_{i,t} + \text{Fixed Effects}_{i,s,t} + \varepsilon_{i,s,t},$$

where $D_{i,s,t}$ is an indicator of whether the consumer i living in state s has a delinquent credit account at the end of quarter t, $RiskScore_{i,t}$ is the standardized Equifax Risk Score for that consumer, and Fixed Effects always include borrower and state-by-time fixed effects as well as a borrower-specific linear time trends. The distributed lags $\text{BAN}_{s,t,k}$ take values one only in the k'th period since a state implemented a PECS ban, except for $k = 5$ which is one for all periods 5 or more quarters after the state banned PECS and zero otherwise.

Figure 1: Effect of PECS Ban on Vacancies and Delinquencies

tween productivity and repayment rates through an ongoing costly effort decision that affects a worker's future productivity. Since patient people are more willing to expend effort to raise future productivity in exchange for the expected future benefit of higher wages, they invest, on average, more than impatient people.

We make assumptions on matching and wage determination to keep the labor market model tractable and rationalize the observed use of PECS by employers. First, we assume that all matches have positive surplus, so low-score matches generate low, but still positive, expected profits. Since our results depend on the job finding rate's sensitivity to the score rather than the exact point in the matching process at which the job finding rate is determined, we find this assumption innocuous.[7] Second, we assume that productivity is immediately learned by employers once a match occurs. This assumption is shared by Jarosch and Pilossoph [26]

[7] If the surplus from a low-patience/productivity worker was negative, then they would not be hired at all. With a positive surplus, they simply face a longer expected duration of unemployment.

who study the effect of unemployment duration on job-finding rates by changing potential employers' expectations of a worker's productivity.[8] This is partially a technical assumption to retain tractability by avoiding asymmetric information during wage bargaining, but also guarantees that the effect of an individual's credit score on her post-employment earnings is small, which is the case empirically. A slower learning process post-match based on changes in the individual's credit report would generate large swings in an individual's earnings when she defaults, which is inconsistent with the small effect on individual earnings estimated in Dobbie, et. al. [17]. Finally, we use post-match Nash-Bargaining rather than a competitive search model with pre-match contracts requiring commitment as in Guerieri, et. al. [20] designed to perfectly separate types since that would obviate the use of costly PECS in the first place. The fact that we observe PECS conditioning on credit scores suggest that such perfectly separating contracts are hard to design in the real world.

Motivated by the above mentioned empirical evidence of an interaction between labor and credit markets, we also develop a rich model of credit markets with adverse selection. We model the credit market as a sequence of short-term loans, linked by the worker's score, which enters as a state variable representing the market belief that a worker is the high type (and therefore low risk) given her history of repayments. Rather than assume a given form of credit contracts, as in Chatterjee, et al. [9], we use the contract design framework of Netzer and Scheuer [37]. This framework determines both interest rates and credit supply as the unique equilibrium of an extensive form game played between lenders competing to make loans to borrowers with private information about their default rates.[9] Our framework allows for the endogenous design of a rich set of equilibrium contracts ranging from fully separating to cross-subsidized separating to pooling, conditional on a borrower's score. Specifically, contracts posted by lenders depend on the borrower's score because high-risk borrowers may be cross subsidized through lower interest rates, while higher scores relax credit constraints for low-risk borrowers. A PECS ban can affect individual repayment incentives and therefore the equilibrium credit market contracts (i.e. both interest rates and the supply of credit).

We then use our model as a laboratory to assess the effect of a policy that bans PECS (i.e. an economy where employers must ignore applicants' credit histories in the hiring decision). A

[8]We allow credit histories to signal productivity, but do not use employment histories while Jarosch and Pilossoph allow employment history to signal productivity, but not credit histories. An important aspect of credit reports is that a third party maintains them, so a job applicant cannot distort them like they could job histories (i.e. by excluding information).

[9]Netzer and Scheuer apply their extensive form game to the Rothschild and Stiglitz [40] insurance model rather than a borrowing and lending model like our own. Fundamentally, however, our models are within the same class of principal-agent problems with adverse selection in which the principal's marginal rate of transformation between contract terms is higher whenever the low-risk agent takes the contract and there is a single-crossing property on agent preferences over the contract terms. The first key feature of this game is that an equilibrium always exists. This would not be the case for low scores (i.e. when there are few low-risk borrowers) in the competitive framework of Rothschild and Stiglitz [40]. We detail how to alter their proofs for our model in Appendix B.1.

PECS ban has both direct and indirect effects on the equilibrium. First, as expected by policy makers, there is a redistribution of labor market opportunity (and therefore welfare) from high to low credit score workers, which in equilibrium also translates into a redistribution from high to low productivity workers. This directly reduces matching efficiency by eliminating the ability of employers to recruit from a less adversely selected pool of applicants. Furthermore, the welfare effects of a PECS ban differ by age even for workers with a low default propensity, since they are born with much worse credit than their average later in life. Second, there is an indirect effect on repayment that lowers welfare for everyone. When credit scores are not used in the labor market, workers lose some of their incentives to repay debts. This leads to higher interest rates and less borrowing. This general equilibrium cost of PECS bans has not been considered by policy makers, even by those who advocate on behalf of lower income households with bad credit.

We proceed as follows. In Section 2, we place our paper in the context of the literatures on private information in both credit and labor markets. In Section 3 we describe the economic environment and in Section 4 we define and characterize equilibrium for our adverse selection environment as well as compare it to a full information version. In Section 5 we calibrate the economy and describe properties of the adverse selection equilibrium such as a poverty trap and quantify labor market inefficiencies. In Section 6 we study the positive and normative consequences of a ban on using credit checks in the labor market.

2 Related Literature

Almost all of the previous work focusing on the use of credit market information to screen job applicants (i.e. PECS) is on the empirical side. Bartik and Nelson [3] use a statistical discrimination model to study the impact of PECS bans on different racial groups. They find that bans significantly reduce job-finding rates for Blacks. Similarly, Ballance et. al. [2] find that employment falls for younger workers and Blacks in states that ban PECS. These findings are consistent with PECS bans reducing the match quality of newly hired job applicants in affected groups (more high match-quality applicants are rejected and more low match-quality applicants are hired after the ban). Friedberg et. al. [18] estimate an increase in job-finding rates for financially distressed households following PECS bans, which highlights the distributional effect of these laws and provides a key elasticity that our quantitative model matches.

While there is a growing structural literature on asymmetric information in unsecured consumer credit markets with default, we make a methodological contribution to this literature by endogenously determining both credit and labor market outcomes in markets with adverse selection.[10] Specifically, we include labor market search frictions and endogenous wages via

[10]Some closely related papers that deal with private information in the credit market only include Athreya,

bargaining, as in Mortensen and Pissarides [34], along with information revelation in the match as in Jarosch and Pilossoph [26]. This endogenizes potential income losses from default (via a lower credit score) which is taken as exogenous in the earlier structural default literature.[11]

Furthermore, we employ a novel equilibrium concept in the credit market. This equilibrium contract design framework, studied by Netzer and Scheuer [37], is the robust sub-game perfect equilibrium of a sequential game between firms competing to make short term loans to borrowers with private information about their default propensities. The constrained efficient equilibrium allocation of this game solves an optimization problem with incentive compatibility constraints for each type of borrower. We make a methodological contribution to the static model of Netzer and Scheuer by introducing a dynamic Bayesian type score upon which contracts are conditioned every period so that an individual's credit access varies over time in response to past behavior. The salient feature of this equilibrium concept is that competitive lenders endogenously choose *both* the level of debt *and* the price at which it is offered in contrast to offering a risk adjusted competitive (break even) price for each *given* level of debt as in, for instance, Chatterjee, et. al. [9]. This allows for a rich array of contracts ranging from separating to pooling across scores rather than assuming a given form of contract.[12] Our use of the Netzer and Scheuer equilibrium concept allows us to tractably solve for credit market equilibria with adverse selection, which lets us make a general contribution to the literature on signals from one market incentivizing behavior in other markets.[13]

While we model the effect of credit scores on *labor demand*, a related literature uses changes in an individual's credit history to instrument for credit access in order to estimate the *labor supply* response to credit.[14] Along this dimension, Herkenhoff et. al. ([24], [25]) show that increased credit access leads workers to become more selective in their job search (accept longer unemployment durations in order to obtain higher post-employment wages). If we also modeled the labor supply decision then good credit would have similar effects as in Herkenhoff, et. al. For example, if we modeled search effort for unemployed workers, those with high scores would have a weaker incentive to find a job in order to begin rebuilding their credit history.

Tam and Young [1], Chatterjee, et. al. [9], Livshits, MacGee and Tertilt [31], and Narajabad [36].

[11]For example, default in Chatterjee, et. al. [9] incurs an exogenous loss proportional to the household's income.

[12]Our model differs from Netzer and Scheuer because the risk of default depends on the amount borrowed, which leads to regions of pooling whereas their model always has separating contracts. We discuss this difference in detail below. An alternative equilibrium concept that would also ensure that an equilibrium exists is studied by Guerrieri, et al. [20], which we discuss in Section 4.3. Importantly, there can be large welfare gains to using our equilibrium credit contracts rather than Guerrieri, et al.

[13]An important early paper tying cross-market incentives is the reputation based model of Cole and Kehoe [11] which demonstrated how an exogenous utility loss in the labor market can incentivize sovereigns not to default in the credit market. Such cross-market incentives linked by credit scores are important since credit scores are frequently used to screen in many markets like insurance, rentals, etc. For example, Chatterjee et. al. [8] explore the link between insurance and credit scores.

[14]A related literature studies how financial status (i.e. ability to borrow or dis-save to fund current consumption) affect job-finding rates. Relevant contributions include Chaumont and Shi [15], Krusell et. al. [27], and Lentz and Tranaes [29].

Furthermore, a worker with a high score has a stronger bargaining position, which is reflected in higher equilibrium wages (although we find quantitatively this effect is small).[15]

3 Environment

Time is discrete and infinite. Each period is split into two subperiods (i.e. a beginning and end of the month). The economy is composed of a large number of workers, firms, lenders, and the credit reporting agency.

A newborn starts life unemployed and draws a discount factor in $\{\beta_H, \beta_L\}$, which determines her type $i \in \{H, L\}$. The probability the agent initially draws $\beta_H > \beta_L$ is given by π_H, while she remains of a given type i from period to period with probability ρ_i. A worker's type is private information; type cannot be observed by lenders, credit scorers, and can be observed by the firm only after the worker is hired (i.e. in the production process the firm can observe a worker's productivity).

In any period t, workers have one unit of time in the first subperiod and zero in the second subperiod. They can either be unemployed ($n_t = 0$) or employed ($n_t = 1$), which means they work for a firm. Worker preferences are represented by the function $\mathcal{U}(c_{1,t}, c_{2,t}, n_t) = c_{1,t} + h \cdot (1 - n_t) + \psi c_{2,t}$ with the unemployed getting $\mathcal{U}(0, 0, 0)$ and the employed getting $\mathcal{U}(c_{1,t}, c_{2,t}, 1)$ (i.e. the employed derive disutility from work). We assume that $\psi < 1$ so that workers prefer consumption in the first subperiod to the second (i.e. end-of-month consumption is discounted). Since an unemployed worker does not receive income with which to repay debt, she cannot borrow, and hence her flow utility is simply h.[16]

At the end of a period, the unemployed worker knows whether or not she has found a job for the next period. At this point, she must decide whether or not to exert effort to increase her future productivity by choosing $e_{i,t} \in \{0, 1\}$. She incurs a utility cost of $\phi \cdot e_{i,t}$ and has productivity $z_{i,t+1} = \underline{z} + e_{i,t} \cdot (\overline{z} - \underline{z})$ in the next period where $\overline{z} > \underline{z}$. An employed worker who retains her job makes an identical choice of effort that determines her productivity in the next period. For someone who will be unemployed in $t+1$ there is no benefit to exerting effort since their productivity will not affect their unemployment value and they will have the opportunity to choose effort in the future when they next find a job.

[15] Relatedly, while not focusing on PECS, Dobbie, et al. [17] estimate that annual earnings do not change when a person who filed for chapter 13 bankruptcy has that flag fall off of her credit report after seven years, relative to a person who filed for chapter 7 bankruptcy (whose flag remains for ten years), although they do estimate a statistically significant increase in the probability of being employed after flag removal. We show in Section 5.5 that our calibrated model is consistent with empirical results in Dobbie, et al.

[16] We have assumed linear preferences for tractability since it simplifies the Nash Bargaining problem substantially. If instead there was curvature in the utility function across periods and sub-periods, then banning PECS would have two additional effects beyond what we study. First, PECS bans would reduce welfare for all workers because they worsen intra-period consumption smoothing. On the other hand, workers with a low job-finding rate (i.e. those with low scores, which are primarily $L-$types) in the economy with PECS would have higher marginal utilities of consumption and therefore gain more from the ban than in our baseline model.

An employed worker's residual productivity, $z_{i,t}$, is observable to the firm. Production takes place in two stages: the worker inelastically supplies labor ($n_t = 1$) in the first subperiod which generates output $y_{i,t} = z_{i,t}$ in the second subperiod. The worker and firm Nash bargain over her wage $w_{i,t}$ in the first subperiod to be paid when her effort yields output in the second subperiod. The worker's bargaining weight is λ and her outside option is to walk away, receive h utility from leisure in this period, and to search for another match tomorrow. The outside option for the firm is to produce nothing this period and post another vacancy at cost κ (in equilibrium the firm's outside option will be zero due to free entry). The firm sells its second subperiod output, yielding period t profits of the firm given by $z_{i,t} - w_{i,t}$. After production, the worker and firm may exogenously separate with probability σ.

Since an employed worker is paid at the end of the period, if she wants to consume at the beginning of the period and has no savings, she can borrow Q_t from a lender. When an employed worker borrows in the first subperiod, she is expected to repay the unsecured debt b_t once she is paid in the second subperiod, provided she does not default. In the second subperiod, however, an employed worker receives an expenditure shock, τ_t, drawn from a distribution with CDF $F(\tau_t)$, which is i.i.d. across agents and time. The expenditure shock is unobservable to anyone but the worker. Her choice of whether to repay in the second subperiod $d_t \in \{0, 1\}$ is recorded by a credit reporting agency. If the worker does not repay (i.e. $d_t = 1$) we say she is delinquent at time t and defaults at $t+1$.[17] Since an unemployed worker does not borrow, she has no default decision, which we denote $d_t = \emptyset$.[18]. Default bears a bankruptcy cost Δ in the second subperiod at $t+1$, which corresponds to both direct costs (legal fees), but is also a reduced form for higher costs borne in other markets due to bad credit (for example, higher insurance premiums, as explored in Chatterjee, Corbae and Rios-Rull [8]).[19]

A credit reporting agency records the history of repayments by a worker, which is summarized by a score s_t.[20] This score is the probability that a given worker is type $i = H$ with

[17] The worker defaults on both debt and her expenditure shock. In our model, the worker has no incentive to pay the expenditure shock once she has defaulted on debt.

[18] We assume that unemployed workers do not receive the expenditure shock since they have no income with which to pay it. If an unemployed worker received an i.i.d. expenditure shock, they would default with probability one, which would not provide any new information. However, if they received the shock and defaulted it would reduce the flow utility of being unemployed, which would increase match surpluses and worsen worker's bargaining positions. This would magnify the welfare gains for workers who's job finding rates increase after a PECS ban (most of whom are $L-$types), but also magnify the losses for workers who's job finding rates fall (most of whom are $H-$types).

[19] We focus on defaults due to expenditure shocks rather than unemployment shocks for two reasons. First, we want to highlight how incentives to repay debt from the labor market can affect strategic defaults, whereas an unemployment shock between the first and second subperiods in our model would lead to a non-strategic default. Second, Chakravorty and Rhee [10] report that job loss is the direct cause of only 12.2% of bankruptcy filings, whereas reasons that are more akin to expenditure shocks are reported for a higher share of bankruptcies.

[20] In Appendix C, we consider an extension where the amount borrowed is recorded by the credit reporting agency. For our calibrated parameters and a reasonable upper bound on interest rates, this leads to the same credit contracts as our baseline economy for most borrowers, so the positive and normative conclusions are very similar in the two economies.

discount factor β_H at the beginning of any period t. Given the prior s_t and the repayment outcome $d_t \in \{0, 1, \emptyset\}$, the credit reporting agency updates the assessment of a worker's type to $s_{t+1}(s_t, d_t)$ via Bayes Rule. Since a high-type worker cares about their future ability to borrow more than a low-type worker, repayment is a signal to a scorer that the worker is more likely to be a high type. Our type score s_t is therefore not directly comparable to empirical credit scores such as FICO, which orders repayment likelihood on an index from 300 to 850. However, we can rank people by their expected repayment rate within the model, which allows us to group them into credit ratings (subprime, prime, and super prime) based on their ordering in the population, as in the data.[21]

Since a worker's type influences her productivity and default decisions, but is only observable after she is hired by a firm and is never observed by lenders, a worker's score may be used in hiring and lending decisions. We model pre-employment credit screening (PECS) by segmenting labor markets by the score s_t. We denote the number of unemployed job-seekers with a given score s_t as $u(s_t)$ and the number of firms posting vacancies for such workers as $v(s_t)$. The number of matches arises from a constant returns to scale matching function, $M\big(u(s_t), v(s_t)\big) \leq \min\{u(s_t), v(s_t)\}$. Therefore, an unemployed worker with score s_t matches with a firm with probability $f\big(\theta_t(s_t)\big) = \frac{M\big(u(s_t), v(s_t)\big)}{u(s_t)} = M\big(1, \frac{v(s_t)}{u(s_t)}\big)$. We will assume that a tighter labor market (higher $\theta(s_t)$) increases the job finding rate for workers (i.e. $f'\big(\theta_t(s_t)\big) > 0$). The cost to a firm of posting a vacancy for workers with score s_t is denoted κ and the job filling rate is denoted $q(\theta_t(s_t))$, which is decreasing in tightness (i.e. $q'\big(\theta_t(s_t)\big) < 0$). Future profits of the firm are discounted at rate R^{-1}. Importantly, conditioning the market tightness on score s_t is a simple way of modeling PECS.[22]

There are a large number of competitive lenders who have access to consumption goods in the first subperiod, for which they must pay an exogenously given worldwide interest rate of R in the second subperiod.[23] At the beginning of any period, lenders observe each potential borrower's type score s_t but not the history of their actions.[24] Lenders post a menu of contracts $\mathcal{C}_t(s_t) = \{(Q_{j,t}(s_t), b_{j,t}(s_t))\}_{j=1}^{J}$, each of which specifies an amount to be lent in the first subperiod (i.e. at the beginning of the month), $Q_{j,t}$, and a promised repayment in the second subperiod (i.e. at the end of the month), $b_{j,t}$.[25] Lenders realize that households may default on

[21] This is consistent with the credit rankings approach employed in Chatterjee, et. al. [9].

[22] We think of the matching function as a reduced form way of capturing congestion in labor sub-markets. We will assume that the matching function is unchanged after PECS are banned. However, we acknowledge that a micro-foundation of the matching process could make the parameters of $M(u, v)$ dependent on whether PECS is available.

[23] For notational simplicity, we will develop the model without intertemporal savings, but will assume that $\beta_H \leq R^{-1}$ which, along with the linearity of preferences, ensures that households do not want to save. This assumption narrows our focus to households with little-to-no savings. Furthermore, credit scoring agencies base their assessments on the basis of borrowing and repayment behavior but not savings.

[24] This anonymity assumption, as in Bernanke, et. al. [4] and Carlstrom and Fuerst [6], is analogous to assuming that measure zero borrowers are matched with measure zero lenders at random each period, so that there is zero probability of any given lender meeting the same borrower multiple times.

[25] In theory, J is a choice and any finite number of contracts can be included in the menu. In the equilibrium

their debt and the probability may differ by worker type, which affects their expected profits for a given contract. As in Netzer and Scheuer [37], after posting these menus the lenders observe all other menus posted and then may withdraw from the market at a cost k.[26]

Lenders play a game against one another by posting menus of contracts (including $(0, 0)$ so that a worker need not borrow) for each observable credit score $\mathcal{C}_t(s_t)$. The game has three stages, all of which occur in the beginning of the first subperiod of t:

Stage 1: Lenders simultaneously post menus of contracts.

Stage 2: Each lender observes all other menus from stage 1. Lenders simultaneously decide whether to withdraw from the market or remain. Withdrawal entails removing the lender's entire menu of contracts with a payoff of $-k$ (i.e. it is costly to withdraw).

Stage 3: Workers simultaneously choose the contract they most prefer.

To summarize the information structure, workers observe everything (i_t, s_t, $z_{i,t}$, τ_t). Before hiring a worker, a firm only observes the worker's score s_t, which we refer to as pre-employment credit screening (PECS). After hiring a worker, a firm observes her residual productivity, $z_{i,t}$, and current type i_t. Lenders only observe the worker's score s_t: not the broader history of their previous credit market behavior and nothing from their labor market history (such as past wages or effort choices). The credit reporting agency observes a worker's current score s_t and default decision d_t. Credit and labor markets are segmented in the sense that lenders and scorers cannot communicate with firms who know the worker's type after the hiring decision.

Having described the environment for workers, firms, lenders, and credit reporting agencies, we now describe the timing of actions.

- For an unemployed worker who is currently type i, has score s_t, and productivity $z_{i,t}$ all determined in the previous period:

  First subperiod:

  1.1 Enjoy utility h from leisure $n_t = 0$.

  Second subperiod:

  2.1 Die with probability δ.

  2.2 Type score updated, $s_{t+1}(s_t, \emptyset)$.

of our model, $J = 2$ is enough since there are two unobservable types for each s_t.

[26] The ability to withdraw contracts after observing all others posted is key to ensuring that an equilibrium exists, counter to purely competitive models with adverse selection (this idea is used in Wilson [44] and Miyazaki [33] for labor and insurance markets, while Livshits, MacGee, and Tertilt [31] extend the game-theoretic argument of Hellwig [22] to unsecured credit markets). That the withdrawal of contracts is costly ensures that the equilibrium is unique.

2.3 Remain type i with probability ρ_i.

2.4 Surviving workers with score s_t are matched with a firm in labor sub-market s_t with probability $f\big(\theta_t(s_t)\big)$.

2.5 Choose $e_{i,t} \in \{0,1\}$ at cost $\phi \cdot e_{i,t}$ inducing $z_{i,t+1} = \underline{z} + e_{i,t}\big(\overline{z} - \underline{z}\big)$.

- For an employed worker who is currently type i, has score s_t, and productivity $z_{i,t}$ all determined in the previous period:

  First Subperiod:

1.1 Determine earnings w_t via Nash Bargaining and work $n_t = 1$.

1.2 Choose debt contract $\big(Q_{j,t}(s_t), b_{j,t}(s_t)\big)$ and consume $Q_{j,t}$.

Second Subperiod:

2.1 Output $y_{i,t} = z_{i,t}$ is created, from which earnings $w_{i,t}$ are paid.

2.2 Draw expenditure shock τ_t from CDF $F(\tau_t)$

2.3 Choose whether to default $d_t \in \{0,1\}$ and pay $(1-d_t)(b_{j,t} + \tau_t)$.

2.4 Type score updated $s_{t+1}(s_t, d_t)$.

2.5 Separate from employer exogenously with probability σ and die with probability δ.

2.6 Remain type i with probability ρ_i.

2.7 Choose $e_{i,t} \in \{0,1\}$ at cost $\phi \cdot e_{i,t}$ inducing $z_{i,t+1} = \underline{z} + e_{i,t}\big(\overline{z} - \underline{z}\big)$.

4 Equilibrium

We now provide the decision problems for all agents in recursive form. To that end, we let variable x_t be denoted x and x_{t+1} be denoted x'. Further, to save on notation we denote $s_{t+1}(s_t, d_t)$ as s'_d.

4.1 Worker Decisions

The value function for an unemployed worker of type i and score s is given by

$$U_i(s) = h + \psi(1-\delta)\Big[f\big(\theta(s)\big)\mathcal{W}_i(s'_\emptyset) + \Big(1 - f\big(\theta(s)\big)\Big)\mathcal{U}_i(s'_\emptyset)\Big], \tag{1}$$

where the intermediate value functions $\mathcal{W}$ and $\mathcal{U}$ are defined as

$$\begin{aligned} \mathcal{W}_i(s') &= \rho_i \max_{z' \in \{\underline{z}, \overline{z}\}} \Big(\beta_i W^*_{i,z'}(s') - \phi \mathbb{I}_{\{z'=\overline{z}\}} \Big) \\ &+ (1-\rho_i) \max_{z' \in \{\underline{z}, \overline{z}\}} \Big(\beta_{-i} W^*_{-i,z'}(s') - \phi \mathbb{I}_{\{z'=\overline{z}\}} \Big), \end{aligned} \tag{2}$$

$$\mathcal{U}_i(s') = \rho_i \beta_i U_i(s') + (1-\rho_i)\beta_{-i} U_{-i}(s'), \tag{3}$$

where $W^*_{i,z'}(s')$ is the value function evaluated at equilibrium credit contracts and wages, as described below, the notation $-i$ refers to the other worker type, and $\mathbb{I}_{\{x\}}$ is an indicator function which takes the value one if x is true. The unemployed worker receives current flow utility h and survives until the next period with probability $1-\delta$. She then transits to employment next period with probability $f(\theta(s))$ and remains unemployed with probability $1-f(\theta(s))$. Note that, with no credit market activity, the unemployed worker's score changes only through the Markov process on type. Furthermore, since job-finding rates are identical for both worker types conditional on score and all matches have positive surplus, scores are independent of the length of an unemployment spell or total number of spells. Finally, note that the effort choice that determines future productivity is independent of current productivity.

The value function for an employed worker of type i with current productivity z and score s who has chosen contract (Q, b) and faces wage w is given by

$$\begin{aligned} &W_{i,z}(Q,b,w,s) = Q + \\ &\psi\Big(w + \int_0^\infty \max_{d\in\{0,1\}} \Big[(1-\delta)\Big(V_i(s'_d) - d\psi \mathbb{E}[\beta'|\beta_i]\Delta \Big) - (1-d)(b+\tau) \Big] \Big) dF(\tau), \end{aligned} \tag{4}$$

where we have introduced the intermediate value function:

$$V_i(s'_d) = \Big[(1-\sigma)\mathcal{W}_i(s'_d) + \sigma \mathcal{U}_i(s'_d) \Big]. \tag{5}$$

and $\mathbb{E}[\beta'|\beta_i] = \rho_i\beta_i + (1-\rho_i)\beta_{-i}$. The first line in (4) reflects borrowing $Q(s)$ to pay for first subperiod consumption and the second subperiod wage w payment. The second line in (4) reflects the strategic decision of whether to go delinquent to avoid paying off $b+\tau$ in the second subperiod followed by default which bears bankruptcy cost Δ the following period. Note that the scorer updates her assessment s'_d of the agent's type given the worker's default decision d. Working backwards, we start by noting that workers know their future type, employment status, and score when they choose z'. Furthermore, since productive effort only pays off when employed, a person who knows that she will be unemployed will always set $z' = \underline{z}$, since she will be able to optimize again before starting any future job. We denote the productivity based on the optimal effort choice for somebody who is employed as $z^*_i(s')$.

The next decision, working backwards, is the worker's default choice, taking all other objects (in particular their contract choice) as given. The worker defaults if and only if:

$$\tau > \tau_i^*(s,b) \equiv (1-\delta)\Big[\psi \mathbb{E}[\beta'|\beta_i]\Delta + V_i\big(s_0'\big) - V_i\big(s_1'\big)\Big] - b. \tag{6}$$

Thus, higher debt and higher expenditure shocks make default more likely. Furthermore, a lower current discount factor or a lower value from a good reputation make default more likely.[27] We note that the value of a good reputation is given by $V_i\big(s_0'\big) - V_i\big(s_1'\big)$ and can be large or small based on the size of $V_i'(s)$ or the gain in score from repaying, $s_0' = s_{t+1}(s_t, 0)$, relative to defaulting, $s_1' = s_{t+1}(s_t, 1)$. Using $\tau_i^*(s,b)$, after integrating by parts and some cancelation, this allows us to evaluate the integral in $W_{i,h}$ for given values of (Q, b, w):

$$W_{i,z}(Q,b,w,s) = Q + \psi w + \psi \int_0^{\tau_i^*(s,b)} F(\tau)d\tau + \psi(1-\delta)\Big[V_i\big(s_1'\big) - \psi \mathbb{E}[\beta'|\beta_i]\Delta\Big] \tag{7}$$

We can then write the worker's surplus (i.e. utility when employed versus unemployed) evaluated at the equilibrium contracts $(Q_i^*(s), b_i^*(s))$ as the difference:

$$W_{i,z}\big(Q_i^*(s), b_i^*(s), w, s\big) - U_i(s), \tag{8}$$

where the value of unemployment has the same productivity as the value of employment since this difference is meant to capture the off-equilibrium hypothetical of walking away from a match during negotiation. We use this surplus in bargaining below to determine $w_{i,z}^*(s)$, thereby allowing us to define the equilibrium value functions from above as

$$W_{i,z}^*(s) \quad = \quad W_{i,z}\bigg(Q_i^*(s), b_i^*(s), w_{i,z}^*(s), s\bigg). \tag{9}$$

4.2 Firm's Problem and Wage Determination

Recall that after a firm and worker are matched, the worker's type and productivity choice are observed by the firm. The value function for a firm matched with a worker of type i of current productivity z and current type score s who owes b, for a given wage w is:

$$\begin{aligned} J_{i,z}(w,s,b) \quad &= \quad \psi\Big[z - w + R^{-1}(1-\sigma)(1-\delta)F\big(\tau_i^*(s,b)\big)\mathcal{J}_i\big(s_0'\big) \\ &+ \quad R^{-1}(1-\sigma)(1-\delta)\big[1 - F\big(\tau_i^*(s,b)\big)\big]\mathcal{J}_i\big(s_1'\big)\Big], \end{aligned} \tag{10}$$

[27] Since we assume that discount factors are persistent, we have that $\beta_H > \mathbb{E}\big[\beta'|\beta_H\big] > \mathbb{E}\big[\beta'|\beta_L\big] > \beta_L$. This means that the term $\psi\mathbb{E}\big[\beta'|\beta_i\big]\Delta$ is lower for people who currently have discount factor β_L.

where the intermediate value function $\mathcal{J}_i(s)$ is defined as

$$\mathcal{J}_i(s') = \rho_i J_{i,z_i^*(s')}\Big(w^*_{i,z_i^*(s')}(s'), s', b_i^*(s')\Big) + (1-\rho_i) J_{-i,z_{-i}^*(s')}\Big(w^*_{-i,z_{-i}^*(s')}(s'), s', b_{-i}^*(s')\Big) \quad (11)$$

While s does not add information for the firm's inference about worker type, it influences the worker's bargaining position since it determines their credit contract and hence the worker's flow surplus from being employed. Since Nash Bargaining ensures that the firm receives a constant fraction of the match surplus as in (13) below, the firm's surplus will also depend on s even though the firm knows i and z during bargaining since s affects the worker's probability of finding another job, should the bargaining process break down. Since free entry ensures that the firm's value of posting a vacancy is zero, the firm's surplus from a match is simply $J_{i,z}(w, s)$.

The wage is then determined by generalized Nash Bargaining in which the worker's bargaining weight is λ. The wage solves:

$$w^*_{i,z}(s) = \text{argmax}_w \Big[W_{i,z}\big(Q_i^*(s), b_i^*(s), w, s\big) - U_i(s)\Big]^{\lambda} J_{i,z}\big(w, s, , b_i^*(s)\big)^{1-\lambda} \quad (12)$$

Given that worker utility and firm profits are linear in earnings, expression (12) amounts to a simple splitting rule for the total surplus. The first-order condition on the wage is determined so that firms receive fraction $1-\lambda$ of the total surplus

$$J_{i,z}(w, s, b_i^*(s)) = (1-\lambda)\Big(W_{i,z}\big(Q_i^*(s), b_i^*(s), w, s\big) + J_{i,z}(w, s, b_i^*(s)) - U_i(s)\Big), \quad (13)$$

while the worker's surplus is fraction λ of the total. Note that the current wage does not directly affect the repayment decision or optimal debt choice of a household due to the linearity of preferences. If these choices were to depend on the wage, then the wage would affect both the size of the worker's surplus and the split of the total surplus, creating a nonconvexity that would complicate the analysis.

Firms post vacancies in labor "sub-markets" indexed by an unemployed worker's score s so that labor "sub-market" tightness is given by $\theta(s)$.[28] The expected profits from posting a vacancy must be equal to the cost of the vacancy in equilibrium:

$$\kappa = R^{-1} q\big(\theta(s)\big)\Big[s\mathcal{J}_H(s) + (1-s)\mathcal{J}_L(s)\Big]. \quad (14)$$

This means that market tightness will be higher for workers with higher scores as long as the

[28] Our sub-markets are indexed by score rather than contract terms as in the models of directed search. A form of block recursivity, as in Menzio and Shi [32], exists when firms can screen using scores because the score corresponds to the fraction of good types with that score and hence firms do not need to know the entire distribution of workers over scores to evaluate the expected value of posting a vacancy in that sub-market.

discounted expected profits of employing an $H-$type worker is larger than an $L-$type. As a result, workers with higher scores will experience higher job finding rates.

4.3 Lender's Problem and Credit Contract Determination

Lending markets are segmented by s and are open to people with those scores. Since s corresponds to the share of $H-$type borrowers with that score, it is equivalent to the exogenous fraction of the $H-$type from the static model studied by Netzer and Scheuer [37]. Invoking their Proposition 2, for sufficiently small $k > 0$ (i.e. $k \to 0$), the unique equilibrium to the lending game for credit sub-markets with score s is the two-contract menu $\{(Q_H(s), b_H(s)), (Q_L(s), b_L(s))\}$ that solves the following constrained optimization problem (which we will refer to as the "Miyazaki-Wilson" problem, which characterizes the Netzer and Scheuer equilibirum):

$$\max_{\{Q_H,b_H,Q_L,b_L\}} Q_H + \psi \int_0^{\tau_H^*(s,b_H)} F(\tau)d\tau \tag{15}$$

s.t.

$$s\Big[-Q_H + R^{-1}F\big(\tau_H^*(s,b_H)\big)b_H\Big] + (1-s)\Big[-Q_L + R^{-1}F\big(\tau_L^*(s,b_L)\big)b_L\Big] \geq 0 \tag{16}$$

$$Q_L + \psi \int_0^{\tau_L^*(s,b_L)} F(\tau)d\tau \geq Q_H + \psi \int_0^{\tau_L^*(s,b_H)} F(\tau)d\tau \tag{17}$$

$$Q_H + \psi \int_0^{\tau_H^*(s,b_H)} F(\tau)d\tau \geq Q_L + \psi \int_0^{\tau_H^*(s,b_L)} F(\tau)d\tau \tag{18}$$

$$Q_L + \psi \int_0^{\tau_L^*(s,b_L)} F(\tau)d\tau \geq \max_b R^{-1}F\big(\tau_L^*(s,b)\big)b + \psi \int_0^{\tau_L^*(s,b)} F(\tau)d\tau. \tag{19}$$

The Miyazaki-Wilson problem (15)-(19) says that the credit contract for a worker whose score is s is designed to maximize the utility of the $H-$type (low-risk) borrower subject to profitability, incentive compatibility, and participation constraints. The first constraint (16) says that the lender must make non-negative profits on the contract for each score. The first term is the profit (or loss) per the $H-$type borrowers' contract times the number of $H-$type borrowers with score s while the second term is profit (or loss) for the $L-$type borrowers' contract times the number of $L-$type borrowers with score s. Note that (16) does not rule out cross-subsidization. The second and third inequalities ((17) and (18)) are incentive compatibility constraints. For instance, (17) says that $L-$types must choose the contract designed for them rather than the one designed for $H-$types. The final constraint (19) says that an $L-$type must get at least the utility from a credit contract that breaks even and maximizes her utility. That is, the equilibrium contract must give the $L-$type at least her utility from her least cost separating contract, and will deliver strictly more utility if the contract cross subsidizes $L-$types.

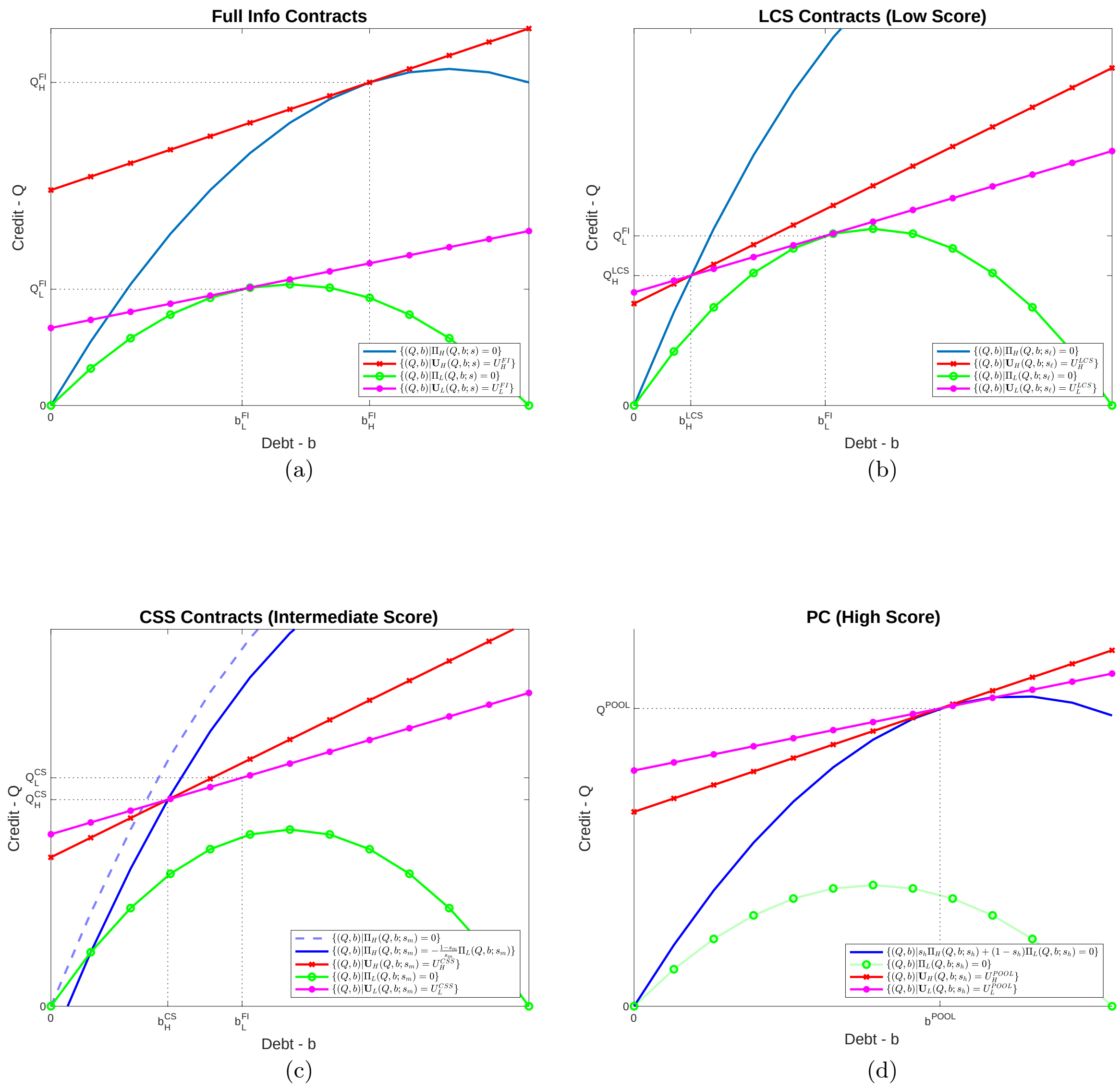
We note some special properties of the Netzer-Scheuer equilibrium concept and its allocations that solve the Miyazaki-Wilson problem, under the assumption that $H-$types have a lower default probability than $L-$types (which arises in equilibrium for our calibrated model). First, we need to solve the model for all scores, which would not be possible in purely competitive models (as in Rothschild and Stiglitz [40]). In a competitive model there would be no equilibrium for a score close enough to one, whereas an equilibrium always exists in the Netzer-Scheuer environment.[29]

Second, the allocation arising from the Miyazaki-Wilson optimization problem can be one of three types: least cost separating (denoted LCS), cross-subsidized separating (denoted CSS), or pooling (denoted PC). Unlike a purely competitive equilibrium, cross-subsidization can occur in a Netzer-Scheuer equilibrium because lenders can withdraw their contracts. If another lender posted a contract that cream-skimmed (i.e., attracted only $H-$type borrowers) then the lender posting the cross-subsidizing contract would make losses and withdraw for sufficiently low k. $L-$types would then choose the cream-skimming contract, which would then cease to make profits.

Third, to match data, we want a model in which workers care about their future scores because their score improves credit contract terms (lower rates or looser constraints) and the fact that credit contracts are cross-subsidizing or pooling for high scores ensures this. This would not be the case in a model in which the credit contracts were always least-cost separating, such as the competitive search model of Guerrieri, Shimer and Wright [20].[30] In that case, an individual's future credit contracts would be independent of their score, which means that credit scores provide no independent incentive to repay current debts.

[29] The standard argument for non-existence in Rothschild and Stiglitz is simple. A competitive equilibrium cannot include a pooling contract, since lenders could "cream skim" $H-$types by posting a contract with a slightly tighter borrowing constraint but lower interest rate. On the other hand, if there were very few $L-$types and all other lenders were offering separating contracts with borrowing limits then a lender could post a pooling contract and attract the entire market at a profit. Hence, there would be no competitive equilibrium.

[30] Their equilibrium concept also has search frictions and contract posting in the credit market and hence an extra endogenous variable. Their framework is directly comparable with the least-cost separating contracts in our work if the cost of posting credit contracts was taken to zero.



Notes: Green circled are zero-profit curves for $L-$type in each figure. Dark blue solid are zero-profit curves for $H-$type in Figures (a) and (b), but conditional zero-profit curve for $H-$type in Figure (c) (i.e. zero profit less the subsidy to $L-$types) and the pooled zero-profit curve for Figure (d). Lighter dashed blue in Figure (c) is the zero-profit curve for $H-$types. Pink dotted are $L-$type indifference curves. Red x'd are $H-$type indifference curves.

Figure 2: Possible Credit Market Contracts with Full and Private Information

Finally, the Netzer-Scheuer equilibrium concept ensures that credit market allocations are always statically constrained efficient. In our calibration, most workers are $H-$types in the stationary equilibrium and have scores in the region where the LCS contract is dominated by either the CSS or PC contracts, so the welfare gains from using the Netzer-Scheuer equilibrium rather than one with least-cost separating contracts for every score can be substantial: for our calibrated parameters, the ex-ante welfare of a person born into an economy with our baseline credit contracts is 0.5% higher than being born into an economy with least-cost separating contracts for all scores.

In order to understand how type score s affects the credit contract, we first consider the full-information allocation and then demonstrate the general form of optimal constrained allocations that arise for different scores. The full-information allocation is shown in Figure 2a. The full information contract maximizes an employed borrower type i's utility subject to zero expected profits on the type i contract. This corresponds to maximizing $Q_i+\psi\int_0^{\tau_i^*(s,b_i)} F(\tau)d\tau$ (as in (15)) for each type i, subject to $Q_i \leq R^{-1}F(\tau_i^*(s,b_i))b_i$ (as in (16)). Graphically, this gives us indifference curves with slopes $\frac{dQ_i}{db_i} = \psi F\big(\tau_i^*(s,b_i)\big) \geq 0$ and isoprofit curves with slopes $\frac{dQ_i}{db_i} = R^{-1}\big[F\big(\tau_i^*(s,b_i)\big) - F'\big(\tau_i^*(s,b_i)\big)b_i\big]$. For sufficiently large debt, these iso-profit curves are downward sloping because the probabily of default rises quickly enough that the lender's zero-profit amount of lending begins to fall even for higher debt promises, which is analogous to the debt price falling to zero in Chatterjee, et. al. [7]. Since for a given (s,b), $\tau_L^*(s,b) < \tau_H^*(s,b)$, the slope of the $H-$type indifference curve is greater than the slope of the $L-$type. Furthermore, since the interest rate on these contracts is given by $\frac{b_i}{Q_i}$, the interest rate can be seen as the inverse of the slope of a ray from the origin to the contract point. Contracts are determined for the $H-$type by the tangency of the solid blue curve and red x'd line and for the $L-$type by the tangency between the green circled curve and pink dotted line. The $H-$type chooses more debt and receives a lower interest rate on this debt since she is less likely to default. But then, if type was private information, an $L-$type would choose the $H-$type's contract, violating incentive compatibility in (17).

Figure 2b-2d show three different types of allocations that can arise under private information. Figure 2b shows the least-cost separating allocation, in which the $L-$type receives their full-information allocation (the tangency between the green circled curve and the pink dotted line) and the $H-$type's contract is determined by their zero-profit condition and a binding $L-$type incentive compatibility constraint (17) with the $L-$type's participation constraint (19) holding with equality (as illustrated by the intersection of the solid blue curve and the pink dotted line). These types of contracts typically arise for low scores (in our calibrated model, they arise for $s < 0.11$, whereas the median score is 0.85). The $H-$type's contract is distorted because of the binding incentive compatibility constraint of the $L-$type. In particular, the $H-$type receives less debt than the L-type, although her interest rate is still equal to the risk-adjusted break even rate on her loan. This puts the $H-$type on a lower indifference curve than in Figure 2a.

As a worker's score rises the optimal contract typically switches from LCS to CSS.[31] For

[31]We say typically because we cannot prove this in general because a higher score both changes the lender's

CSS contracts, the $L-$type worker's participation constraint (19) is slack, because she still receives the full-information level of debt but pays a lower interest rate (illustrated by Q_L being above the $L-$type zero profit curve in Figure 2c). This moves the $L-$type borrower to a higher indifference curve, while shifting the conditional zero-profit curve for $H-$type borrowers downward by the subsidy to $L-$type borrowers (from the dashed blue to the solid blue curve). The $H-$type borrower's contract is given by the intersection of the $L-$type borrower's new indifference curve and the $H-$type borrower's conditional zero-profit curve. This means that the lender makes a profit on each contract delivered to the $H-$type, which is paid as a subsidy to the $L-$type so that the lender makes zero profits when aggregating over both contracts. The CSS contract delivers more debt to the $H-$type borrower than the LCS contract for the same score, but carries a higher interest rate than the LCS contract. The CSS contract dominates the LCS for intermediate scores ($0.11 \leq s < 0.22$ in our calibration) because the extra interest paid per $H-$type borower to subsidize $L-$type workers is more than offset by the $H-$type's utility gains from receiving more debt (e.g. loosening her credit limit).

The third contract type is pooling (PC), which can arise as s increases further (above 0.22 in our calibrated model). As the interest rate cross-subsidy to $L-$type workers becomes extremely generous, the $H-$type's incentive constraint (18) binds.[32] With so few $L-$type borrowers with a high score, the subsidy *per* $L-$type contract is too generous and the $H-$type borrower would rather have the $L-$-type's subsidized rate, even though this gives her less credit. Therefore both incentive compatibility constraints bind, which means that the contract must be pooling (i.e. each type receives the same debt and interest rate). As with the CSS contracts, pooling contracts generate a profit for the lender on $H-$types and a loss on $L-$types that add to zero. We find this contract by maximizing the utility of the $H-$type borrower subject to the pooled zero-profit condition. Graphically, this is given by the tangency between the $H-$type's indifference curve and the pooled zero-profit curve, as in Figure 2d.[33]

participation constraint and the default thresholds. When we compute equilibria we verify which contract type is optimal and these examples are illustrative of how our contracts change with score.

[32] In some settings, such as the constant risk insurance model in Netzer and Scheuer, the $H-$type incentive compatibility constraint never binds. This is not the case in our model because of our interaction of adverse selection and moral hazard, which means that default rates (and therefore the indifference curves and zero-profit curves) depend on debt for each borrower. In Appendix B.2 we algebraically show the $H-$type incentive compatibility constraint can bind and why it is more likely for higher s.

[33] The formula for the $H-$type's indifference curve is the same as before. The slope of the pooled zero-profit curve is given by $\frac{dQ}{db} = \frac{d}{db}\left\{R^{-1}\left[sF\big(\tau_H^*(s,b)\big) + (1-s)F\big(\tau_L^*(s,b)\big)\right]b\right\}$.

4.4 Type Scoring

Given the prior probability s that a worker is type H, the credit reporting agency forms a Bayesian posterior s'_d the worker is type H conditional on seeing whether she repays (d):

$$s'_0(s) = \frac{\rho_H F\Big(\tau^*_H\big(s, b^*_H(s)\big)\Big)s + (1-\rho_L)F\Big(\tau^*_L\big(s, b^*_L(s)\big)\Big)(1-s)}{F\Big(\tau^*_H\big(s, b^*_H(s)\big)\Big)s + F\Big(\tau^*_L\big(s, b^*_L(s)\big)\Big)(1-s)}, \tag{20}$$

$$s'_1(s) = \frac{\rho_H \Big[1 - F\big(\tau^*_H\big(s, b^*_H(s)\big)\big)\Big]s + (1-\rho_L)\Big[1 - F\big(\tau^*_L\big(s, b^*_L(s)\big)\big)\Big](1-s)}{\Big[1 - F\big(\tau^*_H\big(s, b^*_H(s)\big)\big)\Big]s + \Big[1 - F\big(\tau^*_L\big(s, b^*_L(s)\big)\big)\Big](1-s)}. \tag{21}$$

For an unemployed person, we have

$$s'_\emptyset(s) = \rho_H s + (1-\rho_L)(1-s). \tag{22}$$

Typically a credit score is a measure of how likely the borrower is to repay. In the context of our model, s is a "type" score. In equilibrium, we can map an equilibrium s to a credit score (i.e. the probability of repayment given s) as follows:

$$\Pr\big(d = 0|s\big) = F\Big(\tau^*_H\big(s, b^*_H(s)\big)\Big)s + F\Big(\tau^*_L\big(s, b^*_L(s)\big)\Big)(1-s). \tag{23}$$

4.5 Distributions

We denote the measure of workers of type i over employment status $\ell \in \{0,1\}$ (where 1 denotes employed and 0 denotes unemployed) and with score no greater than s (i.e. the cumulative distribution function) in period t as $\mu_{i,\ell}(s)$. Given $\mu_{i,\ell}(s)$, we can compute $t+1$ measures (denoted $\mu'_{i,\ell}(S)$ for some set of scores S) using decision rules and the updating function. Denoting $\overline{F}(\tau) = 1 - F(\tau)$, we have the following laws of motion for the measures of employed people:

$$\begin{aligned} \mu'_{i,1}(s') &= (1-\delta)\int_0^1 f\big(\theta(s)\big)\Big[\rho_i d\mu_{i,0}(s) + (1-\rho_{-i})d\mu_{-i,0}(s)\Big]\mathbb{I}_{\{s'_\emptyset(s)\le s'\}} \\ &+ \rho_i(1-\delta)(1-\sigma)\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\le s'\}}F\big(\tau^*_i(s, b^*_i(s))\big) + \mathbb{I}_{\{s'_1(s)\le s'\}}\overline{F}\big(\tau^*_i(s, b^*_i(s))\big)\Big\}d\mu_{i,1}(s) \\ &+ (1-\rho_{-i})(1-\delta)(1-\sigma)\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\le s'\}}F\big(\tau^*_{-i}(s, b^*_{-i}(s))\big) + \mathbb{I}_{\{s'_1(s)\le s'\}}\overline{F}\big(\tau^*_{-i}(s, b^*_{-i}(s))\big)\Big\}d\mu_{-i,1}(s) \end{aligned} \tag{24}$$

where $\mathbb{I}_{\{s'_d(s)\le s'\}}$ is an indicator function which takes the value one if $s'_d(s) \le s'$ and zero otherwise.

For the unemployed we have two regions. For scores lower than the population share of high-types (i.e., for $s < \pi_H$):

$$\begin{aligned}
\mu'_{i,0}(s') &= (1-\delta)\int_0^1 \big[1 - f\big(\theta(s)\big)\big]\big[\rho_i d\mu_{i,0}(s) + (1-\rho_{-i})d\mu_{-i,0}(s)\big]\mathbb{I}_{\{s'_\emptyset(s)\leq s'\}} \qquad (25)\\
+ &\quad \rho_i(1-\delta)\sigma\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\leq s'\}}F\big(\tau_i^*(s,b_i^*(s))\big) + \mathbb{I}_{\{s'_1(s)\leq s'\}}\overline{F}\big(\tau_i^*(s,b_i^*(s))\big)\Big\}d\mu_{i,1}(s)\\
+ &\quad (1-\rho_{-i})(1-\delta)\sigma\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\leq s'\}}F\big(\tau_{-i}^*(s,b_{-i}^*(s))\big) + \mathbb{I}_{\{s'_1(s)\leq s'\}}\overline{F}\big(\tau_{-i}^*(s,b_{-i}^*(s))\big)\Big\}d\mu_{-i,1}(s).
\end{aligned}$$

For scores above π_H we must add the newborns who start unemployed with $s = \pi_H$. That is, for $s \geq \pi_H$:

$$\begin{aligned}
\mu'_{i,0}(s') &= \delta + (1-\delta)\int_0^1 \big[1 - f\big(\theta(s)\big)\big]\big[\rho_i d\mu_{i,0}(s) + (1-\rho_{-i})d\mu_{-i,0}(s)\big]\mathbb{I}_{\{s'_\emptyset(s)\leq s'\}} \qquad (26)\\
+ &\quad \rho_i(1-\delta)\sigma\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\leq s'\}}F\big(\tau_i^*(s,b_i^*(s))\big) + \mathbb{I}_{\{s'_1(s)\leq s'\}}\overline{F}\big(\tau_i^*(s,b_i^*(s))\big)\Big\}d\mu_{i,1}(s)\\
+ &\quad (1-\rho_{-i})(1-\delta)\sigma\int_0^1 \Big\{\mathbb{I}_{\{s'_0(s)\leq s'\}}F\big(\tau_{-i}^*(s,b_{-i}^*(s))\big) + \mathbb{I}_{\{s'_1(s)\leq s'\}}\overline{F}\big(\tau_{-i}^*(s,b_{-i}^*(s))\big)\Big\}d\mu_{-i,1}(s).
\end{aligned}$$

4.6 Definition of Equilibrium

A steady-state Markov equilibrium consists of the following functions:

1. Worker value functions, $U_i(s), W^*_{i,z}(s)$, satisfy (1) and (9).
2. Default threshold functions, $\tau_i^*(s,b)$, satisfy (6).
3. Firm value functions, $J_{i,z}(w,s,b)$, satisfy (10).
4. Wage functions, $w^*_{i,z}(s)$, satisfy (12).
5. Market tightness functions, $\theta(s)$, satisfy the free entry condition (14).
6. Credit market contracts, $\{(Q_i^*(s), b_i^*(s))\}_{i\in\{H,L\}}$, satisfy (15)-(19).
7. The updating functions, s'_d, satisfy (20), (21), and (22) .
8. Stationary measures of each worker type over scores, $\mu^*_{i,1}(s), \mu^*_{i,0}(s)$ that satisfy (24) -(26) with $\mu'_{i,\ell}(s) = \mu_{i,\ell}(s) = \mu^*_{i,\ell}(s)$ for $\ell \in \{0,1\}$ and $i \in \{L,H\}$.

4.7 Full Information Equilibrium Characterization

Since we will define matching efficiency relative to the equilibrium outcomes of a full information model, we provide a characterization for that case. We first make parametric assumptions to guarantee that workers borrow within a period and do not save across periods (A.1), that the match surplus of both workers is positive (A.2), and that credit contracts are unique (A.3). We also ensure that all workers have a positive probability of repaying some positive level of debt (A.4) and that all workers default with positive probability (A.5). Finally, we set the cost of productive effort relative to the future wage gain so that the $H-$type always exerts effort but the $L-$type does not (A.6).

Assumption 1 .

A.1 $\psi < (\omega R)^{-1}$, $\beta_L < \beta_H \leq R^{-1}$

A.2 $h < \underline{z}$

A.3 $F''(\tau) \leq 0$

A.4 $F\big(\beta_L(1-\delta)\psi\Delta\big) > 0$

A.5 The support of τ is unbounded above.

A.6 $\beta_H\psi\lambda\big(\overline{z} - \underline{z}\big) \geq \phi > \beta_L\psi\lambda\big(\overline{z} - \underline{z}\big)$.

In Appendix A we define a full-information equilibrium and prove the following:

Theorem 1 *Under Assumption 1, there exists a full information steady-state Markov equilibrium where i is publicly observable that has the following properties:*

$$\theta_H > \theta_L \implies f(\theta_H) > f(\theta_L), \tag{27}$$

$$w_H > w_L, \tag{28}$$

$$F\big(\tau_H^*(b_H^*)\big) > F\big(\tau_L^*(b_L^*)\big), \tag{29}$$

$$z_H^* = \overline{z}, z_L^* = \underline{z}. \tag{30}$$

Importantly, with full information under the parametric restrictions in Assumption 1, $H-$type workers have higher job finding rates (in (27)), have higher wages (in (28)), have lower default rates (29), and have higher productivity (30). Furthermore, our calibrated parameters are all consistent with these assumptions.

5 Quantitative Exercise

To demonstrate how a poverty trap may arise and how markets respond to a policy banning PECS, we compute an equilibrium of our baseline economy and then change the determination of market tightness so that it is independent of type score (consistent with a ban).

5.1 Computing a Private Information Equilibrium

Existence of equilibrium with adverse selection is complicated by the scoring functions, which are not contractions, and the Miyazaki-Wilson programming problem generating credit contracts. In Appendix B we define a computationally feasible version of the private information equilibrium, prove existence for a set of parameters, and provide an algorithm to compute the equilibrium.[34]

5.2 Calibration

A model period is taken to be a month. We use a Cobb-Douglas matching technology so that the job-finding and filling rates are given by $f(\theta) = \theta^{\alpha}$ and $q(\theta) = \theta^{\alpha-1}$. We assume that expenditure shocks have an exponential CDF with a small probability of shock sufficiently large that nobody could pay it. [35] Once these functional forms are set, we must choose parameter values listed in Table 1.

Beginning with the externally calibrated parameters, we set $\beta_H R = 1$ to ensure that $H-$type workers do not save (so neither will $L-$type workers). The risk-free rate, R, is set to match a 2% real cost of funds for lenders, which is chosen to match the average yield on AAA corporate debt relative to CPI inflation from 2010-2020. The probability that a worker retires, δ, is set so that the average agent is in the labor market from age 20 through 65. The matching elasticity α is taken from Petrongolo and Pissarides [38] which is consistent with the midpoint of estimates by Hall [21] (who uses a value of $\alpha = 0.24$) and Shimer [41] (who uses $\alpha = 0.72$).[36] The separation rate from employment, σ, is taken from Shimer ([41]), as is the flow utility during unemployment h. Productivity for those who exert effort, $\overline{z}$, is set to one as a normalization.

Moving to parameters estimated via simulated method of moments in Table 1, we list each free parameter, the value we estimate, and the moment that is most directly related to that parameter in the model. We have chosen moments on credit card debt from various sources. The average credit card rate and share of borrowers in each credit bracket are from

[34] Given our focus on computable equilibria, we discretize the support of the Bayesian forecast as in Chatterjee, et al. [9] in our definitions and proofs. One can use the existence proof for the given parameter space as an initial guess in computing equilibria for other regions of the parameter space.

[35] That is, we assume that $F(\tau) = 0.999\big(1 - e^{-\gamma\tau}\big)$ for $\tau \in [0, \overline{\tau}]$ and $F(\overline{\tau}) = 1$, where $\overline{\tau}$ is a large number that could not be repaid by either borrower type.

[36] Gertler and Trigari [19] also settle on $\alpha = 0.5$.

Table 1: Parameter Values

Parameter	Value	Source or Informative Moment	Interpretation
Externally Calibrated Parameters			
$R-1$	0.17%	Risk free rate 2%	Risk Free Rate
δ	0.21%	45 Years in Market	Worker Exit Rate
α	0.50	Petrongolo & Pissarides (2001)	Matching Elasticity
σ	2.6%	Shimer (2005)	Separation Rate
$\overline{z}$	1	Normalization	Effort Productivity
h	0.4	Shimer (2005)	Unemployed Utility
Internally Calibrated Parameters			
β_L	0.577	Subprime interest rate, CFPB (2015)	$L-$type Discount Rate
Δ	1.524	Prime interest rate, CFPB (2015)	Exog. Default Cost
π_H	48.7%	Super prime rate, CFPB (2015)	Newborn $H-$type %
ρ_H	0.999	Super prime persistence, CFPB (2015)	$H-$ to $L-$ switch rate
ρ_L	0.997	Lifecycle credit rating, CCDR (2023)	$L-$ to $H-$ switch rate
ψ	0.949	Debt to Labor Income, CFPB (2015)	Intra-month Discount
$\frac{1}{\gamma}$	$\frac{1}{9.055}$	Delinq. debt share, CFPB (2015)	Exp. Shock Mean
$\underline{z}$	0.572	Residual Earnings $50-10$, Lemieux (2006)	Wage Distribution
λ	0.49	Post-ban finding rate, Friedberg et al. (2021)	Bargaining Weight
κ	1.468	Job-finding rate, Shimer (2005)	Posting Cost
Implied Parameters			
β_H	0.997	$\beta_H = 1/R$	$H-$type Discount Rate
ϕ	0.12	$\phi = \beta_L(1-\delta)\psi\lambda(\overline{z}-\underline{z})$	Effort Utility Cost

Notes: Externally calibrated parameters are those taken from other sources, directly from data, or normalized. Internally calibrated parameters are found by fitting model moments to empirical moments. The implied parameter β_H ensures no agent desires to save. The implied parameter ϕ is the cost of providing effort and is set to the lowest value to ensure that $L-$types never provide effort and $H-$types always provide effort.

the Consumer Financial Protection Bureau's "Consumer Credit Card Market" report [12]. Note that we rank borrowers by their position in our score distribution in order to map the model to the data, since the model's score and the TransUnion risk score are not directly comparable. The interest rates are "total costs of credit" for each credit bracket in 2015, less 2% for inflation, and reported as monthly rates. These are the most comparable numbers to the model interest rates, since some people pay all balances monthly in the data (and therefore do not pay interest) whereas everyone pays interest in the model.

We also use the CFPB's data to compute credit card debt-to-income and the share of debt that is effectively defaulted on (i.e. more than three months past due). Total credit card debt was \$703 Billion in 2015:Q2. Furthermore, monthly GDP in 2015 was \$1.516 Trillion and according to the Penn World Table, labor's share of income in the U.S. was 0.60 in 2015. We therefore target a debt-to-income ratio of \$703 Billion divided by 0.60×1.516 Trillion. This gives a target of 77.3%. We use the CFPB's reported share of accounts that are more than three months past due as our measure of the delinquency rate and the CFPB's share of super

Table 2: Model Fit

Moment	Data Value	Model Value
Super Prime CC Rate, top 49%	0.87%	0.91%
Prime CC Rate, $34-50\%$	1.17%	1.26%
Subprime CC Rate, $0-33\%$	1.60%	1.53%
Debt to Labor Income	77.3%	77.3%
Delinquency Rate	0.95%	0.98%
Residual Earnings $50-10$	0.57	0.57
Monthly Job Finding Rate	45.0%	45.0%
Persistence of Super Prime Status	85%	86.8%
Bottom 26% Finding Rate Change	30%	30%
Avg. Increase in Credit Ranking	0.26	0.26

Note: Appendix 2 has definitions of model moments.

prime borrowers who remain super prime after two years as our measure of persistence.[37]

Since our perpetual youth model has a fraction of "old" agents who die and are replaced by newborns of a given type (i.e. π_H of $H-$types and $1-\pi_H$ of $L-$types), the model implicitly makes a prediction about average credit scores across one's working life. Specifically, the stationary share of $H-$types satisfies $P_H = (1-\delta)\big(\rho_H P_H + (1-\rho_L)(1-P_H)\big) + \delta\pi_H = 66.4\%$. One then can compute the change in average credit ranking from entry to the labor force (i.e. birth) to retirement (i.e. death). That is, given a person's score we can calculate their percentile in the stationary distribution of scores. We then look at how that percentile changes, on average, over a person's life. As documented in Table 11 of the Online Appendix of Chatterjee, et. al. [9], the increase in average credit ranking from an age bin of $21-25$ to $56-60$ is $0.26 = 0.58 - 0.32$.

Our moments on labor market outcomes are taken from economy wide reports since we do not have merged data with credit scores and earnings or job-finding rates. For the residual earnings $50-10$ ratio, we use the log of median earnings minus the log of the earnings of the tenth percentile, which is reported by Lemieux [28]. We choose λ so that the finding rate for workers in the bottom 26% of credit scores rises by 30% following a ban on PECS.[38] This is in line with estimates by Friedberg, Hynes, and Pattison [18]. Using the Survey of Income and Program Participation, they estimate a 30 percentage point increase in finding rates for the financially distressed following a ban and that the distressed make up 26% of the population living in states that ban PECS. For the job finding rate we use the monthly rate implied by Shimer [41].

[37] The exact value for persistence in the CFPB is approximately 85% based on Figure 24.

[38] A common alternative calibration strategy for workers' bargaining parameter is to impose the Hosios condition, which in our model would be $\lambda = 1-\alpha$. With type switching, there is no way to ensure that workers and firms share the same discount factor for the duration of a match, so the Hosios condition does not guarantee that market tightnesses are efficient even under full information.

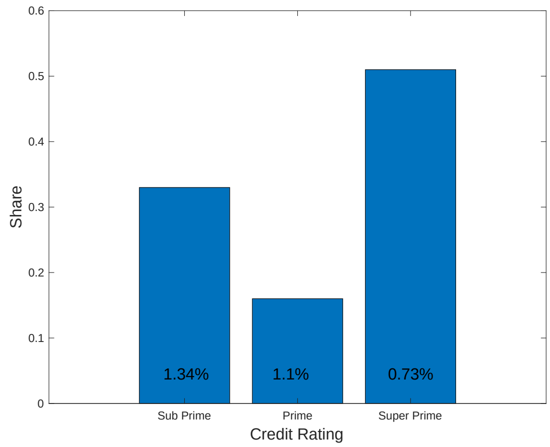
Finally, we set the disutility of providing effort to a value that ensures that $H-$types always exert effort (and therefore have high productivity) whereas $L-$types never exert effort. There is a range of values that ensure this, so we chose the lowest admissible value of $\phi = \beta_L \psi \lambda(\overline{z} - \underline{z}) = 0.12$ (i.e. so that the $L-$type is just unwilling to exert effort but the $H-$type is still willing to do so). Furthermore, because the condition that guarantees that $H-$types exert effort and $L-$types do not holds in both the pre- and post- PECS economies, different values of ϕ in the admissible range have almost no effect on our targeted moments as well as welfare.

5.3 Properties of Stationary Equilibrium

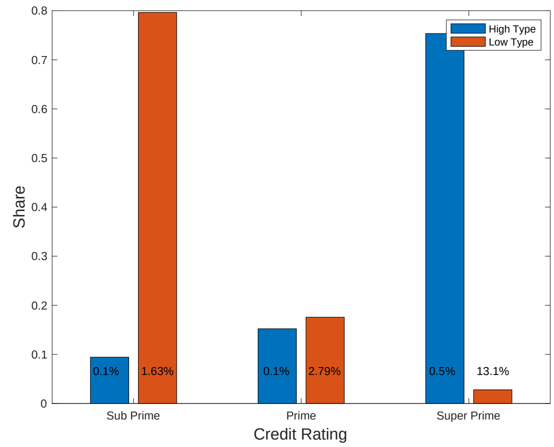
The equilibrium stationary distribution of workers over "type" scores and employment status ($\mu_{i,\ell}(s)$) is determined by the relative solvency and default rates of $H-$type versus $L-$type workers, as well as job-finding rates. Since type scores are not directly observable, we construct a data comparable distribution by sorting borrowers by their default probability and then assigning credit ratings consistent with the empirical shares of households within each rating. This means that as in the data, the bottom third are labeled "subprime", the next 15% are "prime" and the top 50% are "super prime". Figure 3a plots the histogram of workers over credit ratings constructed in this way. While the population shares over credit ratings are defined to match the data, the share of workers of each type within each credit rating is endogenous – it depends on the relative default rates of each worker type in equilibrium. We plot these distributions in Figure 3b, where it is clear that the most $L-$type workers have subprime credit, while less than 10% of $H-$type workers have such poor credit since they only default due to extremely large expenditure shocks. Likewise, roughly 75% of $H-$type workers have scores in the super prime range.

The composition of types over ratings determines the gradient of interest rates, default rates, and debt-to-income ratios with respect to credit rating. This can be understood by considering the average and type-specific default rates by credit rating, which we report in red text in Figures 3a and 3b. The average default rate is falling with credit rating, from 1.34% to 0.73%, but this is because the composition of borrowers in each group is changing, not because an individual always defaults less when her score is higher. For example, the average super prime $H-$type borrower actually defaults five times more than $H-$type borrowers with subprime credit. This is because she receives much less credit when subprime and because she has a stronger incentive to repay in order to build her reputation. In fact, an $H-$type borrower in the prime category has the strongest incentive to repay and therefore the lowest average default rate because default generates the largest drop in score in the updating function in Figure 5b.[39]

[39] We exclude the scores 0 and 1 when plotting these functions because type-switching means that these scores cannot be reached.



(a)



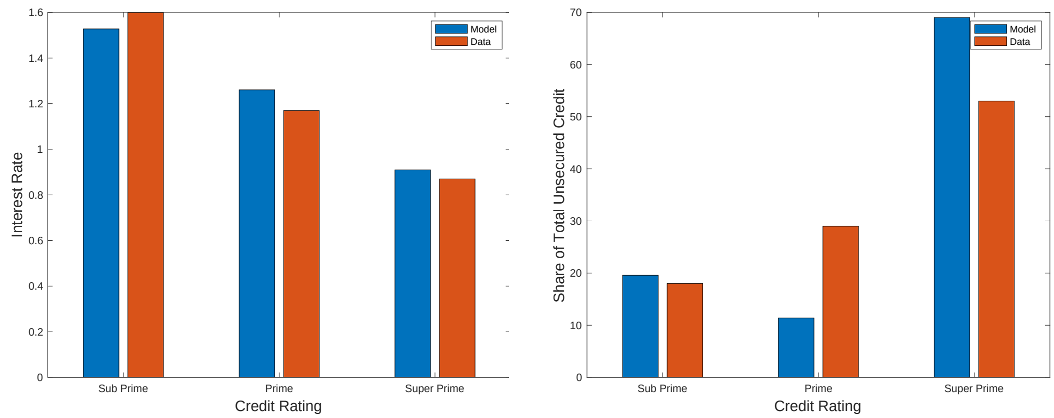
(b)

Notes: Unconditional shares are constructed to match the data, type-conditional are inferred from model. The height of each rectangle represents the fraction of that population with credit score in a given ranking. Black numbers within each histogram rectangle are average default rates for workers in each rating, unconditional on type in Figure 3a and conditional on type in Figure 3a. For example, fraction 0.1 of $H-$types have sub prime credit ratings and they default at a rate of 0.1% per month while 0.8 of $L-$types have sub prime credit and they default at a rate of 1.63% per month.

Figure 3: Histograms over Credit Ratings

Our calibration is also consistent with dimensions of the data not used to fit the model. Figure 4a reproduces the fit of the model's interest rates with data, while Figure 4b shows the shares of debt held by borrowers with each credit rating, both in the data and our model.[40] The fact that credit shares are highest for super prime borrowers is a success of the Netzer and Scheuer equilibrium concept and would not be generated by models in which credit contracts were least cost separating for all scores (since $H-$type households would always have less debt than $L-$type households in such a model to maintain incentive compatibility as is clear in Figure 2b).

[40]The data is from the Consumer Financial Protection Bureau's 2017 credit card report [13].



(a) (b)

Figure 4: Average Interest Rates and Credit Usage by Rating

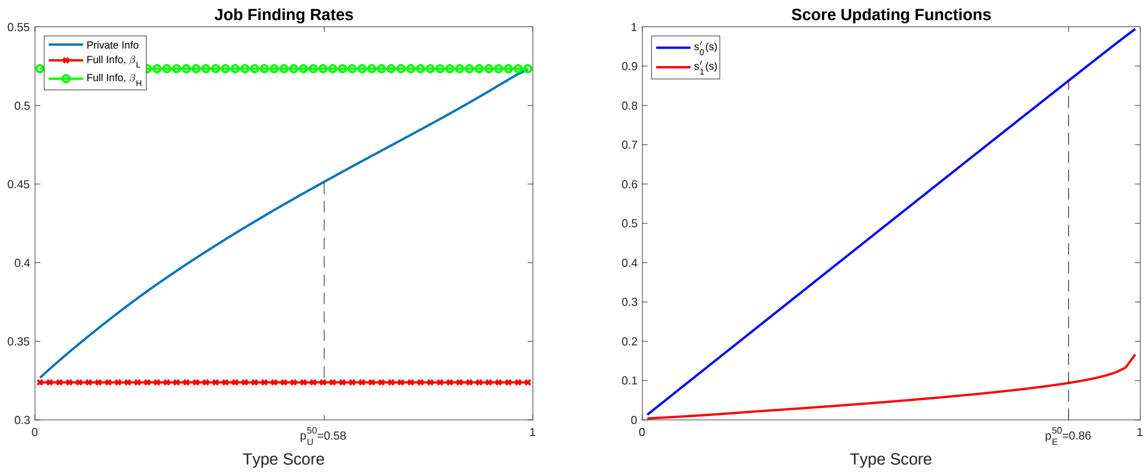
Notes: Model generated interest rates and debt shares relative to data. Figure 4a shows fit of targeted interest rates from model against data. Figure 4b compares debt shares by credit rating from the model and their empirical counterparts, which were *not targeted* in calibration.

The stationary distribution is derived from the law of motion for a worker's employment status and score, which depends on the job-finding rate for unemployed and the average change in score for employed workers. Figure 5a plots the job-finding rate $f(\theta(s))$, which is bounded below by the $L-$type worker's full information rate and above by the $H-$type worker's. The finding rate rises monotonically for scores between zero and one, reflecting the rising surplus associated with $H-$type workers. Since most $H-$types have superprime credit, while most $L-$types are subprime, $H-$types find jobs at a substantially higher rate than $L-$types, on average. Of course, some unlucky $H-$type workers have substantially lower scores than average and therefore experience lower job-finding rates due to being pooled with the $L-$types. The median unemployed worker, marked by p_U^{50} on the graph, has a type score of 0.58 and therefore a job finding rate of 45.1%.[41]

The score updating functions are plotted in Figure 5b, the shape of which can be understood by the relative solvency and default rates of the two worker types. Because both worker types repay with a high probability at all scores, there is very little information revealed by repayment.[42] The score therefore updates very slowly in the positive direction, with $s_0'(s)$ just slightly above the forty-five degree line. However, the default rate for $L-$type workers is up to ten times that of $H-$types. Therefore, observing a borrower default leads to a dramatic downward update of her score, thus $s_1'(s)$ is much lower than s for most scores. The median

[41]Throughout, we use p^x to denote the x^{th} percentile of scores. If we condition on type or status then we use a subscript, so that the notation p_U^x is the score held by x^{th} percentile of the unemployed and p_H^x is the score held by the x^{th} percentile of an $H-$type. Likewise, p_{HU}^x is the score held by the x^{th} percentile of the $H-$type unemployed.

[42]These rates are implied by the interest rate targets, which are low relative to the risk-free rate.



(a) (b)

Notes: Vertical hashed lines mark median scores for unemployed workers in Figure 5a and for employed in Figure 5b. Functions are plotted on score range $0.01 - 0.99$.

Figure 5: Job Finding Rates and Score Updates

employed borrower has a type score of 0.86, implying that a default would reduce her type score to 0.09 (which would make her a subprime borrower).

5.4 Covariance Between Earnings and Credit History

Our model generates a positive covariance between earnings and credit histories through two channels. First, unobservable heterogeneity in underlying types cause differences in both average credit rating and earnings. $H-$type workers have higher earnings than $L-$types for a given credit history and have better credit histories on average creating a positive correlation between credit score and earnings "across" types. Second, a worker of a given type with better credit has a larger threat point, since she knows that she can walk away from a match and find another job with high probability. This means that a better credit score *causes* higher wages "within" each worker type.

In our calibrated economy, prime borrowers earn 29.4% more than subprime on average and super prime earn an additional 17.8% more than prime. However, this is mostly driven by differences in earnings "across" types, since Figure 6 shows that credit rating has little effect on earnings conditional on (i.e. "within") type: moving an $H-$type worker from sub to super prime would increase her wage by 1.3% and for an $L-$type by only 0.4%. On the other hand, Figure 6 illustrates that over 98% of the total increase in wages from subprime to super prime is driven by the across component, since $H-$type workers earn roughly 75% more than $L-$type workers for each credit rating along with the rising share of $H-$types in credit rating.

While there is no direct empirical counterpart to these numbers, there is a strong negative association between adverse credit events and residual earnings. We demonstrate this by estimating an earnings regression from the 2016 Survey of Consumer Finance, in which respondents answered three questions: Q1) whether they were ever delinquent on debt in 2015, Q2) whether they were ever delinquent on debt by more than two months, and Q3) whether they were ever turned down for a loan. We use the answers to these questions (1 = "yes") to estimate the cross-sectional regression

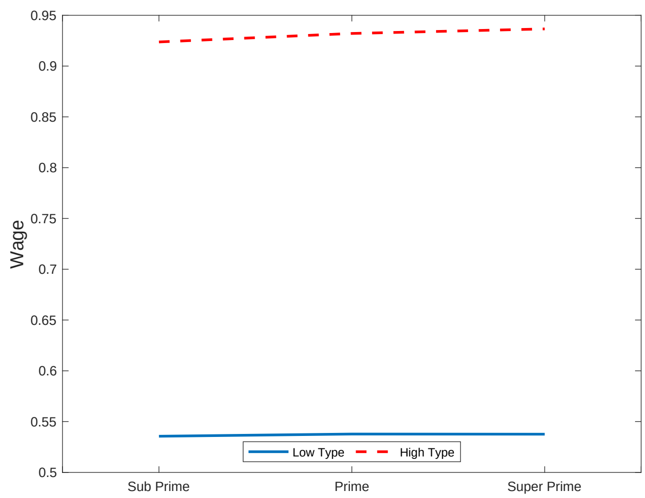
$$\log \text{earnings}_i = \beta_1 Q1_i + \beta_2 Q2_i + \beta_3 Q3_i + \text{controls}_i + \varepsilon_i, \tag{31}$$

where controls include a quadratic function of age as well as dummies for years of education, gender, race, industry, and occupation. Table 3 reports our estimated β coefficients across various specifications. We consistently find a significantly large negative coefficient on adverse credit terms, with a magnitude ranging from 20.3% lower earnings for delinquency alone to 36.7% lower earnings for all three adverse events. These numbers are of similar magnitudes as our model's overall covariance between credit rating and earnings, although we do not know exactly how much these events would move someone's credit rating and these are overall changes that cannot be separated to "within" and "across" cleanly like in our model. we now turn to evidence that the "within" contribution is small empirically (consistent with Herkenhoff et. al. [25] and Dobbie, et. al. [17]), so these large overall effects are likely driven by the "across" component.

	Specification		
	(1)	(2)	(3)
Q1	-20.3^{***}	-14.7^{***}	-13.6^{***}
	(4.9)	(2.8)	(2.6)
Q2		-13.9^{*}	-12.7^{*}
		(1.9)	(1.7)
Q3			-10.4^{**}
			(2.2)
R^2	0.332	0.333	0.333
Obs	4451	4451	4451

Notes: Estimates from equation $\log earnings_i = \beta_1 Q1_i + \beta_2 Q2_i + \beta_3 Q3_i + CONTROLS_i$, where column (1) restricts $\beta_2 = \beta_3 = 0$ and column (2) restricts $\beta_3 = 0$. Questions are 1) were you ever delinquent on debt payments, Q2) were you ever delinquent by more than two months, and Q3) were you ever turned down for a loan. Parenthesis report absolute values of t-statistics. Significance levels represented as $*** = 1\%, ** = 5\%, * = 10\%$.

Table 3: Cross-Sectional Regression of Earnings on Credit Events



Notes: Average earnings by credit rating and worker type. Left vertical axis corresponds to $H-$type workers and right vertical axis to $L-$type workers.

Figure 6: Credit Ratings and Wages by Type

5.5 Empirical Effect of Default on Credit and Earnings

The first piece of evidence for a small "within" contribution to the covariance between credit and earnings is provided by Herkenhoff et. al. [25]. They report the average change in annual earnings for an individual one year before and after the removal of a bankruptcy flag from their credit report. This effectively isolates the effect of credit above and beyond any permanent worker type and turns out to be roughly 1% in their panel data (similar to our model finding that moving from subprime to super prime increases earnings by $0.4\% - 1.3\%$ conditional on type).

Another way of seeing that the "within" component is small is to estimate regressions on data simulated from our calibrated model that are in line with Dobbie, et al. [17]. They use chapter-7 bankruptcy filers as a control group to look at credit and labor market outcomes for chapter-13 filers in the years after the bankruptcy flag is removed from their credit reports. This occurs seven years after default, whereas chapter-7 filers must wait ten years. They find a large improvement in credit outcomes but very little change in labor markets. While we cannot perform their exact exercise because we have only one type of default, we now show that defaults have large effects on an individual's credit access but limited effect on their earnings.

We estimate linear regressions of earnings and credit balances on lagged default using a panel of 10,000 individuals simulated from our calibrated model.[43] That is, we regress log-earnings and borrowing on lagged default after subtracting individual and time fixed effects:

$$100 \times \log(w_{i,t} + 1) = FE_i^w + FE_t^w + \beta^w(-D_{i,t}^7) + \varepsilon_{i,t}^w, \tag{32}$$

$$100 \times \frac{Q_{i,t}}{\bar{Q}} = FE_i^Q + FE_t^Q + \beta^Q(-D_{i,t}^7) + \varepsilon_{i,t}^Q, \tag{33}$$

where $w_{i,t}$ is simulated earnings for individual i in period t, $Q_{i,t}$ is the amount borrowed by that individual which we normalize by mean borrowing $\overline{Q}$. The FE terms are fixed effects in each regression. Note that we negate the default indicators so that coefficients have the same sign as in Dobbie et al, who compare people who have a default flag fall off relative to those who retain the flag. We estimate these regression models on thirty years of simulated data for people with twenty to fifty years of access to credit markets, which is in line with the age restrictions used by Dobbie, et al.

Table 4 shows our point estimates and 95% confidence intervals along with the empirical estimates of Dobbie, et al's.[44] While our model's predicted regression point estimates differ from Dobbie, et al's estimates, the coefficients for both earnings and credit are within their 95% confidence intervals. Our model is therefore broadly consistent with their evidence.

[43] Dobbie, et al. have a sample of 289,000 borrowers. Adding more to our simulation shrinks our confidence intervals, but does not change our point estimates, which remain within their 95% confidence intervals.

[44] Since our estimates from model simulations are of the effect of a default appearing on somebody's credit report, whereas their research design uses the default being removed, we have multiplied our estimates by -1 so that the signs match. For Dobbie, et al's effect of removing default on earnings, we use the estimate from their Table V, column (2) and for the effect on credit we use their estimate from Table III column (2) normalized by the mean in Table III column (1).

Table 4: Panel Regressions of Earnings and Credit on Default

	Earnings	Credit
Model Estimate	1.77%	5.21%
Model C.I.	$[1.52\%, 2.03\%]$,	$[4.92\%, 5.49\%]$
Dobbie, et al. Estimate	0.00%	6.93%
Dobbie, et al. C.I.	$[-1.95\%, 1.95\%]$	$[4.80\%, 9.06\%,]$

Notes: Row labeled "Model" presents β estimates from equations $100 \times \log(w_{i,t}+1) = FE_i^w + FE_t^w + \beta^w D_{i,t}^7 + \varepsilon_{i,t}^w$ and $100 \times \frac{Q_{i,t}}{Q} = FE_i^Q + FE_t^Q + \beta^Q D_{i,t}^7 + \varepsilon_{i,t}^Q$ using panel of 10,000 simulated individuals over thirty years from calibrated model. Row labeled "Dobbie, et al. Estimate" is the negation of one-year ahead estimates of Chapter 13 filers versus Chapter 7 filers in Dobbie, et al. Rows labeled as C.I. are the 95% confidence intervals of each point estimate.

5.6 Poverty Traps

The definition of a poverty trap is not universally agreed upon, so we discuss two possible definitions. The first is a situation in which a worker's experience is made worse due to her credit score relative to an otherwise identical worker. In our case, this happens for the $H-$type households. An $H-$type worker who becomes unemployed with a bad score has a harder time finding a job than one who becomes unemployed with a good score. This leads to further divergence between the two, since the worker with good credit will find a job sooner *and therefore* have an even better credit score in the future. This is because employed $H-$type workers experience an increase in their credit score on average while the unemployed do not borrow and therefore are unable to improve their score through repayment. We say that the $H-$type household is subject to a poverty trap because, on average, she experiences a decrease in her score (relative to being employed) and the decrease in score makes it harder to find a job in the next period.

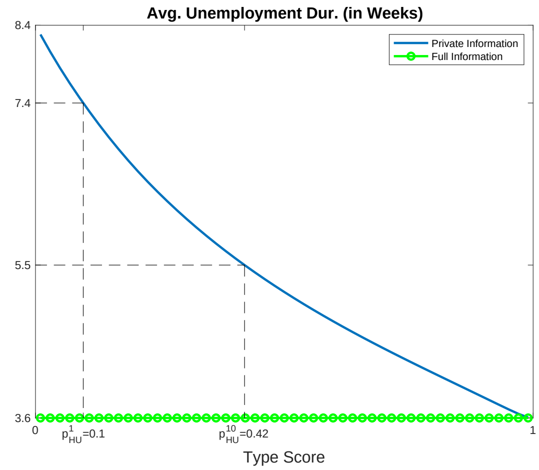
We use two figures to understand how such a poverty trap may arise. Figure 7a uses the job-finding rates (as in Figure 5a) to compute the expected unemployment duration of an unemployed $H-$type household as a function of her score s. It is falling with score, reflecting the fact that $H-$type workers are more productive in equilibrium and tend to have higher scores. Note that there are some $H-$type workers who end up with low scores, illustrated by the vertical bar at the tenth percentile. This is the first part of the poverty trap; an unlucky $H-$type worker with a bad credit history has a hard time finding a job and therefore expects longer unemployment spells than if her score was higher.

We next look at the average change in a worker's score when unemployed relative to when she is employed.[45] Figure 7b plots this function for $H-$type workers. On average, an employed

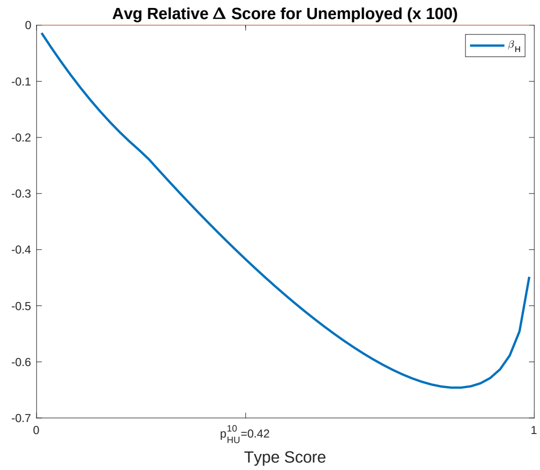
[45] The average relative change in score is defined as:

$$\mathbb{D}(s) = s'_{\emptyset}(s) - F\left(\tau_H^*\left(s, b_H^*(s)\right)\right) s'_0(s) - \left[1 - F\left(\left(\tau_H^*\left(s, b_H^*(s)\right)\right)\right] s'_1(s)$$

The change while unemployed is just due to mean reversion of type while the average change while employed



(a)



(b)

Notes: Figure 7a shows average unemployment duration as function of worker's score, relative to the efficient full information duration for a high-type worker of 3.6 weeks. Hashed lines highlight duration for bottom 1% of the high-type unemployed (7.4 weeks) and bottom 10% (5.5 weeks). Figure 7b plots change in score for high-type individuals while unemployed minus average change in score when employed. Functions are plotted on score range $0.01 - 0.99$.

Figure 7: Poverty Trap for High Types

$H-$type worker experiences a rising score, while her score mean reverts while unemployed. It is evident from the figure that an unlucky $H-$type worker experiences a deterioration in her score relative to if she was employed, which reinforces the longer unemployment duration. Note that the relative change is U-shaped because the expected update when employed is smallest for scores near 0 and 1.

Another way of defining the poverty trap is relative to the full information equilibrium. The idea is that the job-finding rate for a worker with a low score may be strictly lower than if her productivity was observable. Again, consider Figure 5a and compare the finding rates between the private and full information economies. The $H-$type worker experiences a lower job-finding rate for all $s < 1$ while the opposite is true for the $L-$type worker. For example, the bottom quintile of unemployed $H-$type workers have scores below 0.53 and a job-finding rate below 44%, which is 8.1% below the full information rate of $H-$type workers. Private information has the opposite effect for the $L-$type workers, 10% of whom have scores above 0.56 and therefore finding rates above 45%, which is 12% above their full information rate.

The extent of the poverty trap relative to full information depends on the $H-$type worker's score. Using the score percentiles in Figure 7a we can say that the poverty trap adds only one day to the median $H-$type worker's unemployment duration, but over 7 days for the 25^{th} percentile, and just under 13 days for the lowest decile of $H-$type job seekers. The bottom

is the probability of repaying times the positive update plus the probability of defaulting times the negative update. Thus, the relative average change is $\mathbb{D}(s)$.

one percent of these workers have a poverty trap of nearly a month.

A useful summary of the labor market impact of default can be computed as the present value of wages conditional on repayment minus the same value conditional on default. We compute these measures for each worker type and employment status, as well as the unconditional average, amortize them over 10 years (which is the average duration that Chatterjee, et. al. [7] assume a default flag affects a borrower's earnings and access to future credit) and report this measure relative to the average wage in Table 5. Our model generates expected wage losses from default through two mechanisms. First, the job-finding rate falls due to a lower score. Second, the worker's bargaining position becomes weaker and therefore their wages fall even conditional on being employed. The average across all worker types, scores, and employment statuses amounts to 0.85% of earnings in each month for ten years, with $H-$type workers suffering 1.03% and $L-$type only 0.49%. Interestingly, our endogenous estimate of 0.85% accounts for roughly half of the small loss imposed following bankruptcy for an average of 10 years in Chatterjee, et. al. [7] who consider a proportional loss (denoted γ in their paper) of 1.9%.

Table 5: Present Value of Wage Losses From Default

	Employed	Unemployed	Overall
$H-$type (β_H)	1.00%	1.56%	1.03%
$L-$type (β_L)	0.46%	0.84%	0.49%
Overall	0.90%	1.39%	0.85%

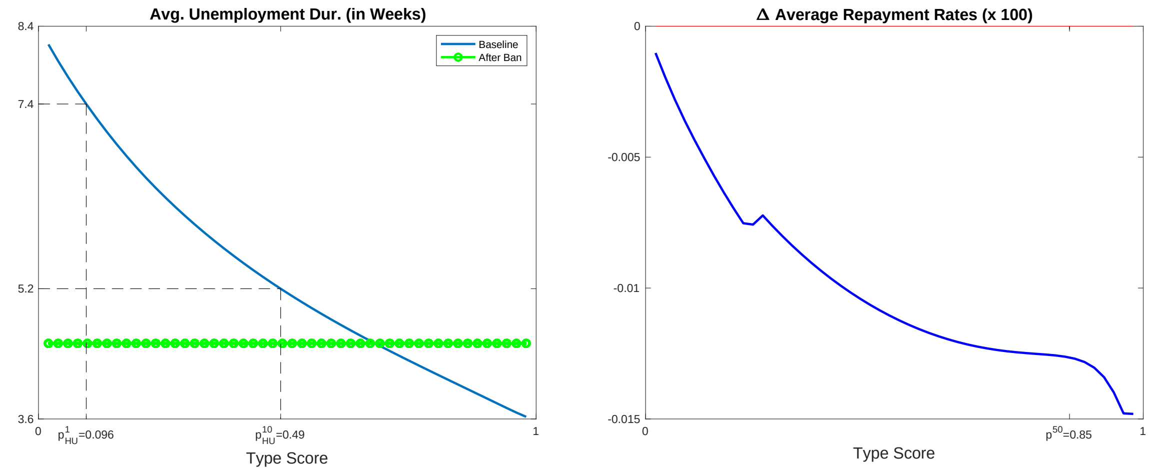
5.7 Labor Market Efficiency

We define a measure of labor market efficiency by considering the average difference between each worker type's average finding rate in the economy with private information relative to the full information economy. For the $H-$type households in the calibrated economy, the monthly job-finding rate averages 49.1%, which is 3.2 percentage points lower than the efficient rate of 52.3%. On the other hand, $L-$type households have an inefficiently high job-finding rate. In the calibrated economy their monthly job-finding rate is 38.8%, which is 6.5 percentage points higher than the efficient rate.

6 Policy Experiment: Banning Credit Checks

We now solve the economy with the same parameters, except that vacancies cannot be conditioned on a worker's score which implies market tightness θ is independent of s.[46] That is,

[46] We assume that the matching function remains the same when there is only one labor market as when each score has a separate labor market. If the inability to use scores in hiring leads employers to use a noisier signal



(a) (b)

Notes: Model's predictions for unemployment duration and repayment rates in response to PECS ban. Functions are plotted on score range $0.01 - 0.99$.

Figure 8: Equilibrium Effects of Ban

we substitute $q(\theta)$ for $q(\theta(s))$ in the free entry condition in (14). While market tightness and the job-finding rate are therefore independent of s (and independent of β_i as before), match surplus and therefore bargained wages still depend on s since the worker's score affects her bargaining position post match. Credit markets operate as before the ban, except that the workers' incentives to repay endogenously fall; since default (which lowers a worker's credit score) does not affect the worker's job finding rate, there is less punishment associated with default.

6.1 Changes in Labor and Credit Market Variables

The ban's effect on aggregate variables can be seen in Table 6. The average job-finding rate rises as we move from the PECS stationary equilibrium to the one without it (from 45.0% to 46.8%). This occurs for three reasons. First, the finding function is concave in scores, which means that the finding rate rises mechanically from pooling, keeping all other equilibrium variables constant. Second, the equilibrium unemployment pool's composition shifts towards higher productivity workers following the ban. This shift occurs because high-score workers find jobs at a higher rate in the baseline economy and the $H-$types are disproportionately represented in the upper credit ratings. Therefore, the $H-$types have shorter unemployment durations and make up a smaller fraction of the unemployed pool than they do in the population as a whole. Once the ban goes into effect, they have the same job-finding rate as everyone else, and

instead, then this could effectively reduce the number of matches that occur for the same number of job seekers and vacancies. If so, then there would likely be an additional reduction in welfare for all types than in our baseline economy.

Table 6: Equilibria with Different Information

Moment	Baseline			After Ban				Full Info.		
Type	β_H	β_L	Avg.	β_H	β_L	SR Avg.	Avg.	β_H	β_L	Avg.
Job Finding Rate (%)	49.1	38.8	45.0	46.8	46.8	44.6	46.8	52.3	32.2	45.3
Interest Rate (%)	0.98	1.54	1.17	0.99	1.55	1.18	1.18	0.90	1.77	1.19
Debt to Income (%)	78.50	73.06	77.30	78.15	72.26	76.81	76.82	93.54	18.30	85.19

Note: This table shows the job-finding rates, interest rates, and debt-to-income values in the stationary long-run equilibrium corresponding to our baseline economy with PECS, the economy without PECS, and the economy with full information. In addition, it shows the short-run (SR) averages after the PECS ban occurs, as we describe in the text.

therefore their share of the unemployed is the same as their share of the population. Third, and most interestingly, eliminating PECS weakens the threat point of $H-$type workers since they can no longer leverage their high scores to find a job quickly if the bargaining process was to break down. This means that employing an $H-$type worker with a high score (which represents the vast majority of them) is more profitable without scores.

At first glance, a higher job-finding rate in the no-PECS stationary equilibrium may seem counter to the empirical results in Figure 1a. This result can be reconciled with the data by noting that the data is unlikely to represent a new stationary equilibrium, but instead represents the incentive of firms to post vacancies for a distribution of unemployed workers that reflects the PECS equilibrium and wages that are unlikely to have fully adjusted. Therefore to account for the short run impact of the PECS ban, we calculate the number of vacancies that firms would post if they: 1) could no longer use scores to screen, 2) drew from the initial stationary distribution of unemployed when posting a vacancy, and 3) could only bargain for new wages each month with probability $\frac{1}{12}$ (so wages remained fixed for a year on average). In this situation, firms post 4.1% fewer vacancies, which is just under the estimated decline of 5.5% in Cortes, et al. As a result, the average job finding rate falls from 45% to 44.6% as shown in Table 6 in the column SR Avg. Furthermore, we calculate the short-run effects on default rates and other credit market outcomes are the same as the long-run effects (to the second decimel place), as can be seen by comparing SR Avg. and Avg.

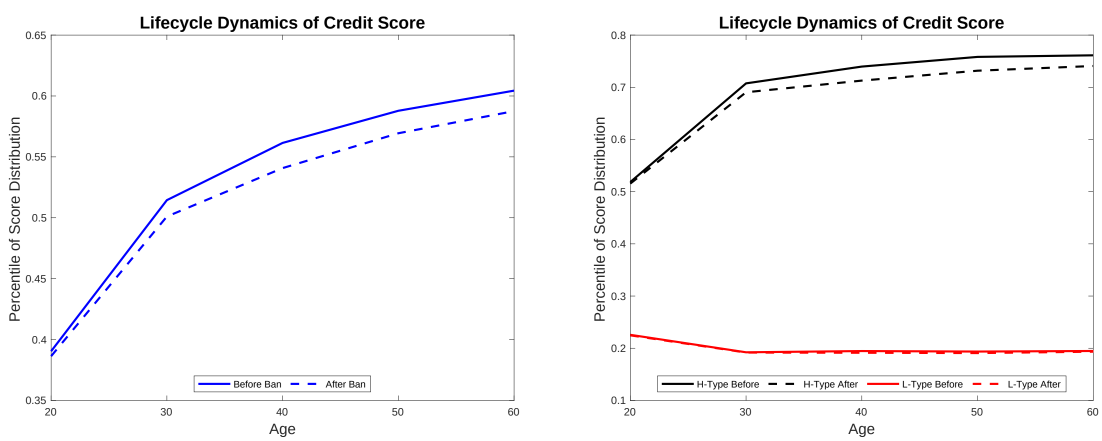
The effects on job-finding rates differ substantially across the score distribution, as seen in Figure 8a.[47] We find that the job finding rate for workers with very low scores rises substantially, which causes the average duration of unemployment for the bottom quartile of workers to fall by 30%. This is consistent with Friedberg, Hynes, and Pattison [18]. They estimate that workers in the bottom 26% of financial health enjoy a 30% rise in job finding rates when PECS bans are enacted at the state level.

The ban also affects the credit market through the repayment decisions of borrowers as

[47] We plot changes in the expected unemployment duration in Figure 8a since it is in more easily interpretable units (weeks). The relationship with the job finding rate is monotone - a higher finding rate implies a lower duration.

seen in both Figure 8b and Table 6. The average interest rate rises from 1.17% to 1.18% as the average default rate rises from 0.98% to 0.99% since borrowers are no longer incentivized to repay in order to find jobs faster in the future.[48] While the average effects are rather small, these incentive effects differ more substantially across worker types and scores. Specifically, the $H-$type's repayment rate falls more than the $L-$type's, since they respond to dynamic incentives more in the first place. Since $H-$types have higher scores on average, Figure 8b shows larger declines in repayment as scores rise.[49] This is consistent with the empirical evidence from Figure 1b, where we found the largest declines in repayment rates for people with higher scores. The new stationary equilibrium therefore features less separation of worker types by credit score (i.e. more workers of each type in the prime rating rather than $L-$types in subprime and $H-$types in super prime).

The ban affects workers by changing equilibrium labor and credit market functions, which in turn affect dynamics of credit ratings. Since the dynamic incentive to repay falls, especially for $H-$types, there is less information generated by observing a default. Figure 9a demonstrates the effect on scoring over an agent's working life - there is a much more gradual increase in the average credit ranking as the worker ages. This is all driven by $H-$types, who converge toward the highest credit ranking more slowly due to their default rates becoming more similar to the $L-$types post ban. Importantly, this illustrates that a labor market PECS ban can spill over to the informativeness of credit rankings over one's working lifetime.



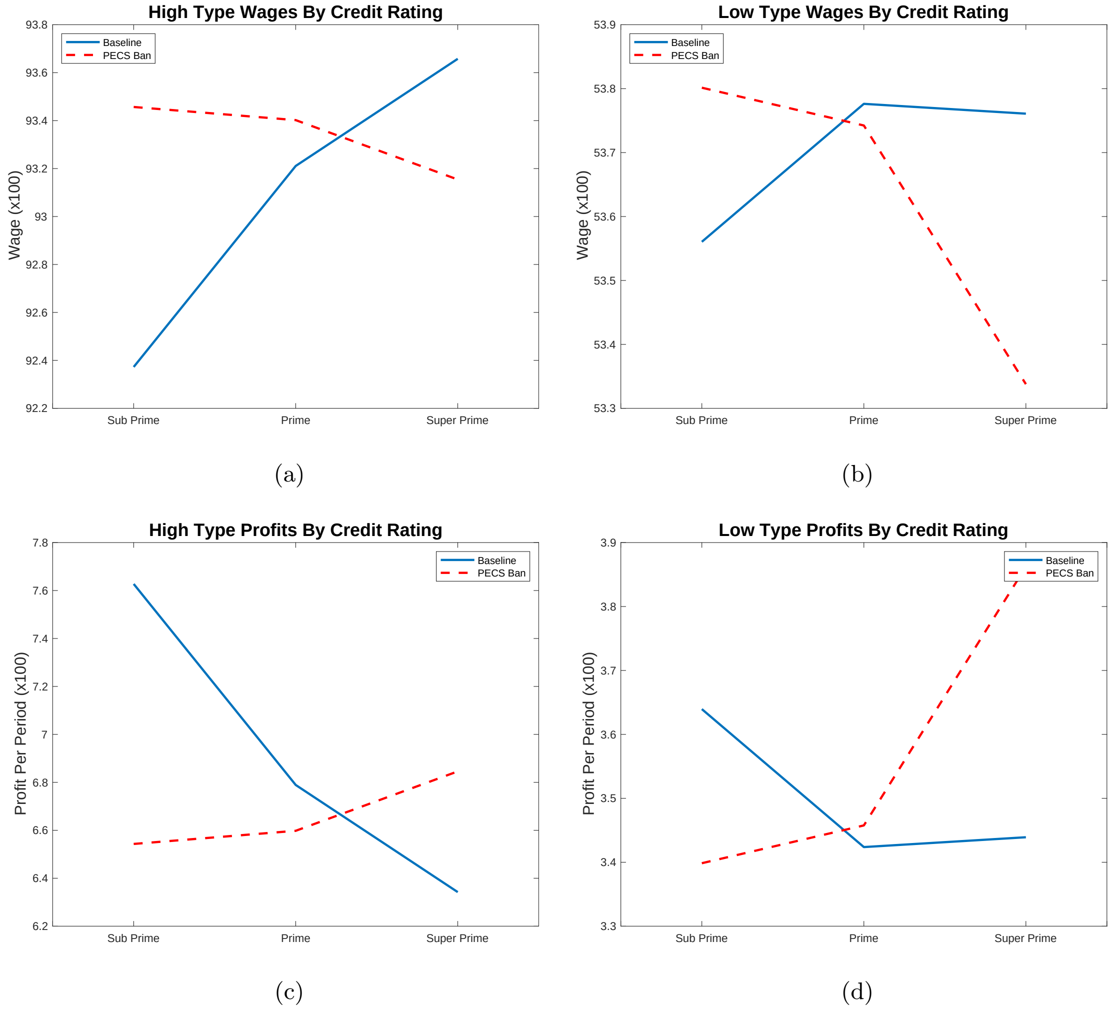
(a) (b)

Notes: Lifecycle paths of average percentile of score distribution. Unconditional average on left and conditional by type on right. Solid lines are in stationary equilibrium before the PECS ban and dashed lines are after. Upper lines in right figure are for $H-$types and lower lines are for $L-$types.

Figure 9: Effect of Ban on Credit Rating

[48]The small region of non-monotonicity in Figure 8b begins as credit contracts switch from LCS to CSS and ends as they shift from CSS to pooling.

[49]Note that the change in default rate is zero at both $s = 0$ and $s = 1$ since these are absorbing scores and therefore the dynamic incentives to repay are zero for both types in both the baseline economy and the one with PECS bans.



Notes: Wages and post-match expected discounted profits by worker type and credit rating before PECS ban and after.

Figure 10: Effect of PECS Ban on Bargaining

6.2 Changes in Wages and Profits

Banning pre-employment credit screening also affects the size and split of rents after a match has occurred by affecting a worker's bargaining position. We demonstrate this in Figures 10a-10d. Prior to the ban, there is generally a positive effect of credit rating on wages for both worker types and, likewise, a downward effect on profits. Wages depend on the score because it affects both the match surplus and the worker's threat point from negotiation breaking down because a higher score translates to better credit market allocations and a higher job-finding rate of unemployed workers. A better credit contract increases the surplus while a higher finding rate reduces the match surplus but improves the worker's threat point.

The net effect typically causes wages to rise with credit score for a given worker type. Of course, the unconditional wage rises even faster with credit rating since $H-$type workers have higher wages at all scores. The opposite profile appears in profits - conditional on worker type, profits are highest for workers with bad credit ratings. On the other hand, the level of profits is strictly higher for $H-$type workers than for $L-$types, due to their higher labor productivities, which generates the positive profile of vacancies with respect to score.

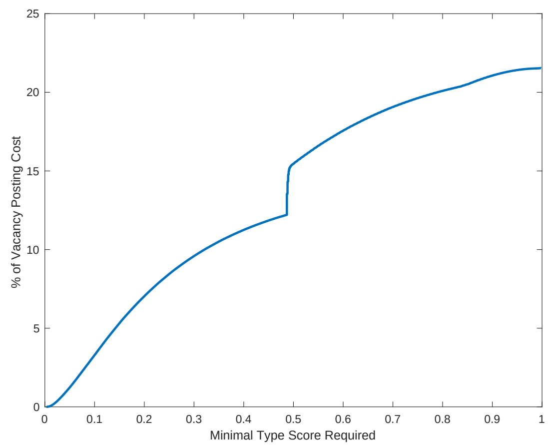
Once the ban goes into place, job finding rates are no longer score specific, which means that a worker's outside option is less affected by her score. This leads to a near complete flattening of the wage profiles in Figures 10a and 10b and profit profiles in Figures 10a and 10b.[50] Relative to the baseline, this causes a decline in wages for workers with high scores but a rise in wages for subprime and prime, while profits move in the opposite direction.

Finally, post-match expected discounted profits rise on average after the ban because workers' threat points change. As shown in Figures 10c and 10d, the post-match profitability of employing a worker of either type with super prime credit rises, since these workers experience a deterioration in their threat points. On the other hand, the post-match profitability of employing a worker with prime or subprime credit falls since these workers experience an increase in their threat points (i.e. they no longer suffer from low job finding rates due to their bad credit). On net, however, post-match profits rise after the ban, since almost all $H-$type households have excellent credit (post-match profits rise in 53.3% of matches overall, which is driven by an increase in 81.9% of matches with $H-$type workers).

Note that since there is no change in the cost of posting a vacancy, ex-ante expected profits from posting a vacancy is zero in both environments. The above increase in average post-match profits occurs after the ban goes into effect through changes in the equilibrium threat point of workers, which are taken as given during bargaining. This result does not mean that firms would choose to ignore PECS in an environment where they are not banned. In particular, if equilibrium threat points are consistent with all other firms choosing to ignore PECS, then it is individually rational for a measure-zero firm to conduct PECS in order to raise post-match expected discounted profits. We demonstrate this point in Figure 11, where we calculate the expected profit in excess of the cost of posting a vacancy for a firm that is allowed to use PECS. The x-axis represents the minimal score that someone must have to apply to the deviating firm's job when every other firm is posting unconditional vacancies. The higher is the minimal score, the higher the probability of getting an $H-$type worker, which raises expected profits. Since this curve is always positive and increasing in the minimal score, a firm would always want to deviate to using PECS if no other firm was doing so. Therefore, not using PECS cannot be an equilibrium when they are allowed by law.[51]

[50] Quantitatively, our wage profiles are flat to three decimal places and therefore appear as such in the plots, but do still vary in theory. Likewise, the discounted profit lines are quite flat, though less so than wages.

[51] The jump in expected profits at $s = \pi_H$ in Figure 11 is because newborns enter as unemployed workers $s = \pi_H$.



Notes: Profit from posting a vacancy only open to applicants with score above “Minimal Type Score Required” when all other firms are posting unconditional vacancies.

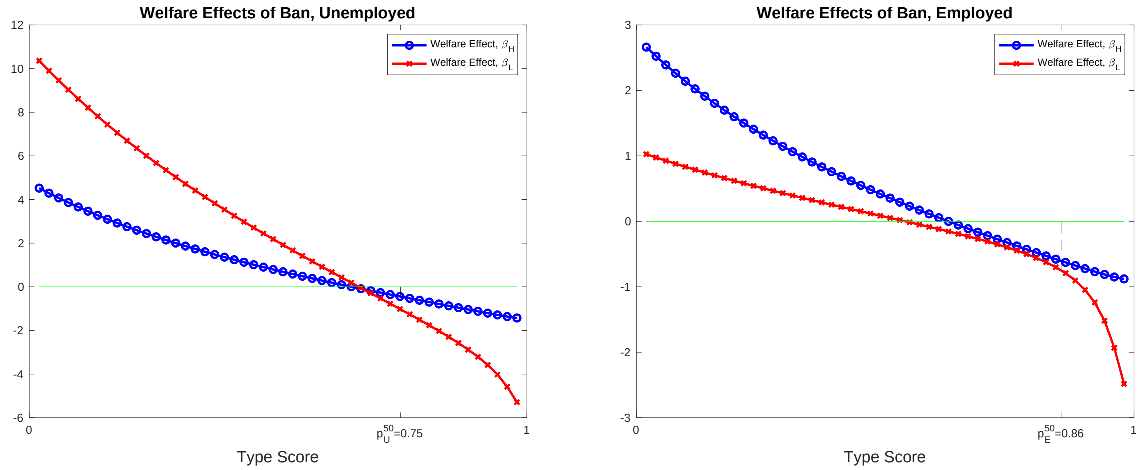
Figure 11: Gain From Using PECS

6.3 Changes in Matching Efficiency

It is important to note that, while banning PECS eliminates the poverty trap, most of the people with inefficiently low finding rates (i.e. unlucky $H-$type workers) experience lower job-finding rates. For example, the pre-PECS ban equilibrium is nearly separating, with only 18.2% of $H-$type workers carrying scores below $s = 0.68$, which is the threshold for which durations fall post-ban (as seen in Figure 8a). On average, $H-$type workers experience 2.2 days more unemployment following the ban, which is relatively large when compared to the effects of much broader labor market policies. For example, Card and Levine [5] estimate that a thirteen week extension of unemployment benefits increases average unemployment duration by roughly one week.[52]

This exercise shows that banning PECS may actually increase the average job-finding rate, but still does so at the cost of labor market efficiency measured relative to the full information job-finding rate. This can be seen by the small fall in the median job-finding rate, which is due to a decline in the job-finding rate for almost all of the $H-$type workers (who are $P_H = 66.4\%$ of the population in our baseline economy and tend to have high scores). In fact, the unemployment rate for $H-$type workers *rises* from 5.3% to 5.6% following the ban. Relative to the efficient job-finding rate, the $L-$type worker's finding rate is 8.0% higher after the ban (in levels, it rises from 38.8% to 46.8%). On the other hand, $H-$type workers are now pooled with more low productivity workers and therefore experience a more inefficiently low finding rate than in the economy with PECS. Their finding rates falls from 49.1% to 46.8%, which is 5.5% lower than the efficient level. When we average over these absolute changes, the

[52]We make this comparison to put the magnitude into context, not because they are directly comparable policies. Specifically, unemployment benefits likely work through labor supply rather than demand, as in our model.



(a)

(b)

Notes: Consumption equivalent welfare effects of being in an economy with PECS ban relative to baseline economy, by worker type, score, and employment status. Positive numbers represent a gain from the ban, negative numbers represent a loss.

Figure 12: Welfare Effects of Ban

ban moves job-finding rates away from their efficient levels by 13.5%.

6.4 Changes in Welfare

We now study the net effect of the ban on welfare.[53] For the unemployed, Figure 12a shows how the direct change on market tightness and finding rates affects these workers. Workers with low type scores experience a gain in welfare, since they experience a higher job finding rate than when firms can discriminate based on score.[54] Furthermore, $H-$type workers gain more since they put a higher weight on finding a job due to their higher β. The welfare gains are falling for both worker types as scores rise, eventually becoming negative for those with high scores. Likewise the welfare effect is positive but falling for employed workers, as seen in Figure 12b. On average, $L-$type workers gain from the ban and $H-$type workers lose, however there are some $H-$types who gain because they have bad scores and some $L-$types with good scores who lose. The effects (both positive and negative) are magnified for unemployed workers since any change in job finding rates affects them immediately. In aggregate, only 40% of the stationary distribution's population have a welfare gain from banning PECS, with most $H-$types, who comprise a majority of the population, losing and most $L-$types gaining; therefore, the ban would be voted down if brought up in a referendum.

[53] See the appendix for the definition of these welfare measures.

[54] We can evaluate the welfare effects for workers at each score, even if the theoretical measure of them is zero. For example, we calculate the value function of high-type workers at $s = 0$ and low-type at $s = 1$ when we solve the model. However, we omit these points from our plots because there are no workers who actually experience them in equilibrium.

	High-Type	Low-Type	Ex Ante
Employed	-0.53%	0.50%	
Unemployed	-0.60%	6.29%	
Average	-0.53%	0.91%	1.57%

Table 7: Avg. Welfare Effects

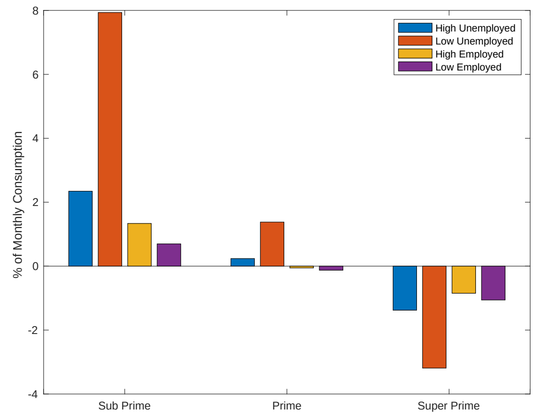


Figure 13: Welfare Effects by Credit Rating

We summarize the average welfare effects by type and employment status in Table 7.[55] The long-run distributional effects are substantial, with $H-$type workers losing slightly on average (equivalent to 0.53% of consumption each month), but $L-$type workers gaining a lot, especially the unemployed (they gain 6.3% of consumption). However, if we consider the ex-ante lifetime utility of a worker before her type is realized (i.e. who has a π_H probability of being a high type and will enter the economy as unemployed), then there is a welfare gain of 1.6% of monthly consumption for a worker born into the economy without PECS, relative to being born into an economy that allows them. This is because newborns have low credit rankings ($s = \pi_H$ corresponds to the bottom 34% of the score distribution) and are unemployed, so both $L-$types and $H-$types have a slight welfare gain from being born into the economy without PECS. This highlights the heterogeneity of welfare effects across type and age via one's position in the credit ranking distribution. For example, there is an interesting conflict between young and old workers with regards to a PECS ban.

Even within a worker type and employment status, there is substantial heterogeneity in the welfare effect of banning PECS. We illustrate this in Figure 13, which shows that subprime workers gain from banning PECS no matter the worker's type or employment status, while the opposite is true for super prime workers, who lose from the ban regardless of type or status. In each case, the unemployed gains/losses are larger than the employed because they are immediately affected by changes in the job-finding rate, whereas the employed are only affected by the ban's general equilibrium effects.

[55] If private information persisted after hiring, then we would expect reduced expected profits due to overpaying the low-productivity type. This would make scores more valuable than in our baseline model. So, getting rid of PECS would have bigger negative effects on matching and welfare losses would be larger than what we are estimating.

7 Conclusion

As the difference-in-difference empirical results in Figure 1 document, a ban on PECS leads to a decline in vacancies in those affected occupations and a relative rise in delinquencies for those with better credit ratings. We provide a framework to link labor and credit markets to understand such facts by extending the workhorse Diamond-Mortensen-Pissarides model to include ex-ante private information about worker productivity, while also building a novel framework for including credit scores when borrowers have private information about their repayment rates. The model provides a theoretical foundation for why employers may use credit histories in the hiring process and how this practice can create a poverty trap.

Combining these two microeconomic models highlights the connection across markets in the presence of private information and shows how a direct labor market policy change spills over to the credit market which further affects labor outcomes. Our model allows us to calculate the endogenous income losses associated with default which is typically taken as exogenous in models of consumer default like Chatterjee, et. al. [9].

Our model complements the empirical literature on the effect of banning PECS by addressing the effect on unmeasurable outcomes – labor market efficiency and welfare. We show that these effects can be large even when the aggregate effects of banning PECS on measurable outcomes may appear small (see Table 6). Banning PECS increases the job finding rate of low-score workers, but these workers are predominantly low productivity. The opposite is true for high-score workers, who mostly have high productivity: they experience an increase in average unemployment duration of 2.2 days following the ban. While efficiency is unequivocally reduced, the welfare effects are more nuanced. High risk ($L-$type) workers, who tend to have relatively bad credit, gain from the ban, the equivalent of 0.91% of monthly consumption. Low risk ($H-$type) workers, who are the majority, lose 0.53% of monthly consumption. Furthermore, there is a disagreement between young and older workers: in the stationary distribution, where many households have earned high scores as they've aged, only 40% of the population gains from the ban, but young workers with low scores tend to gain, so that ex-ante a newborn person would prefer the economy without PECS. We conclude that policy makers should consider the trade-off between equity and efficiency when considering PECS bans.

8 Data and Code

The data and code underlying this research is available on Zenodo at
https://dx.doi.org/10.5281/zenodo.11285273

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