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Lending Standards and Borrowing Premia in Unsecured Credit Markets*

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Abstract

Using administrative data from Y-14M and Equifax, we find evidence for large spreads in excess of those implied by default risk in the U.S. unsecured credit market. These borrowing premia vary widely by borrower risk and imply a nearly flat relationship between loan prices and repayment probabilities, at odds with existing theories. To close this gap, we incorporate supply frictions – a tractably specified form of lending standards – into a model of unsecured credit with aggregate shocks. Our model matches the empirical incidence of both risk and borrowing premia. Both the level and incidence of borrowing premia shape individual and aggregate outcomes. Our baseline model with empirically consistent borrowing premia features 45% less total credit balances and 30% more default than a model with no such premia. In terms of dynamics, we estimate that lending standards were unchanged for low risk borrowers but tightened for high risk borrowers at the outset of Covid-19. Borrowing premia imply a smaller increase in credit usage in response to a negative shock, which this tightening reduced further. Since spreads on loans of all risk levels are countercyclical, all consumers use less unsecured credit for insurance over the cycle, leading to 60% higher relative consumption volatility than in a model with no borrowing premia.

JEL Codes: E21, E32, E44, E51, G12, G21, G22

Keywords: Bankruptcy, borrowing premia, consumer credit, business cycles.

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1 Introduction

The U.S. unsecured credit market has experienced extraordinary growth and transformation in recent decades, with credit balances and bankruptcy filings increasing substantially.[1] A growing literature finds that individuals and households, particularly those with low income and wealth, rely on access to this market for a variety of financing needs.[2] Similarly, a rich body of theoretical and quantitative research has made significant advancements in analyzing unsecured credit markets in environments with household heterogeneity.[3] A particular focus of this existing work has been on how loan size choices and the evolution of idiosyncratic and aggregate states map into probabilities of default. Such theories deliver a linear relationship between loan prices and default probabilities (yellow line, Figure 1): default risk premia account fully for the spread between the benchmark interest rate and the loan rate. As a corollary, heterogeneity in loan prices comes solely from variation in default risk.

In stark contrast, we document using administrative data that the elasticity of interest rate spreads on unsecured loans with respect to default probability is much smaller than such models predict (blue line, Figure 1). This implies the presence of large borrowing premia – interest rate spreads *in excess of* risk premia – in the unsecured credit market. For 2019, we estimate that these premia average 11.1 percentage points (pp), and their magnitudes decline as default risk increases. These premia point to supply frictions absent from existing quantitative models of unsecured credit. How do these frictions and borrowing premia shape credit market outcomes and welfare in the cross-section and over the business cycle?

To bridge this gap between data and theory, we propose an incomplete markets, heterogeneous agent model with aggregate shocks which incorporates tractable supply frictions to generate borrowing premia in the unsecured credit market. The model features a flexible form of "lending standards" which we estimate to match the observed profile of borrowing premia. In the presence of these premia, changes in default risk do not map directly into changes in the price of a loan. We then use this quantitative model to analyze in detail the effects of the overall level, cross-sectional incidence, and dynamic responses of borrowing premia. We find that each of these three facets shapes the role of unsecured credit for economic outcomes and welfare in the cross-section and over the business cycle.

[1] See, for example, Livshits et al. (2010).

[2] For example, Gross and Souleles (2002) and Sullivan (2008) find that unsecured credit is used to smooth consumption: households whose income declines accumulate more debt and declare bankruptcy more often. Furthermore, Herkenhoff et al. (2016) find that self-employment increases with credit limits and credit scores. Following bankruptcy, individuals are more likely to start a new business and borrow extensively.

[3] For work in stationary settings, see, for example, Athreya (2002), Athreya et al. (2009), Livshits et al. (2007, 2010), Chatterjee et al. (2007), Chatterjee et al. (2020). For work in non-stationary settings, see Nakajima and Rios-Rull (2019).

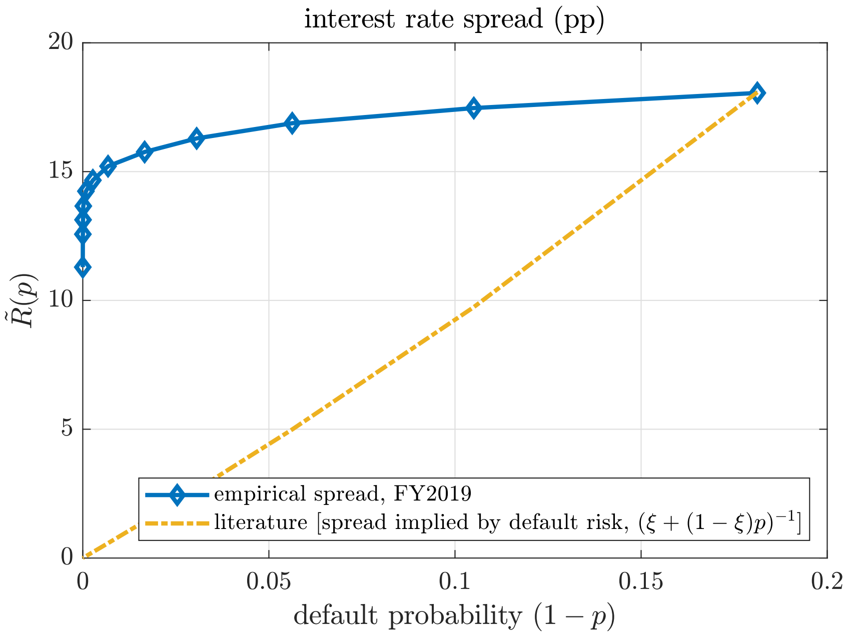

Figure 1: **Interest rates in the data and implied by the literature**

Notes: The blue line in this figure is constructed using the combined Equifax and Y-14M sample described in Section 2.2. The yellow line uses the workhorse theoretical framework described in Section 2.1, where p is the probability of repayment and ξ is the rate of recovery in the case of default.

Our analysis provides three main takeaways. First, our data reveal that borrowing premia are large on average; decline with borrower risk; and increase in downturns, especially for high risk borrowers. Second, we demonstrate with our model that these premia induce changes in the composition of unsecured credit across the distribution of borrower risk. Specifically, they lead to a credit market in which one-quarter of total balances are accounted for by very high risk (default probability above 10%) borrowers. Third, we show that borrowing premia reduce both the average level of debt and the increase in debt in response to a negative economic shock, resulting in significant welfare losses. We proceed as follows.

First, in Section 2 we combine two large administrative data sets – Y-14M and the FRBNY Consumer Credit Panel (Equifax) – to document the relatively flat relationship between interest rate spreads and default probability in Figure 1. Using a "wedge" measurement approach adapted to workhorse unsecured credit pricing theories,[4] we use these spreads to quantify borrowing premia which are large and decline with borrower risk. We estimate that premia are 11.1 pp on average and range from 14.2 pp for FICO scores near 800 to 0.5 pp for FICO scores near 620. This declining pattern is puzzling because it implies that the difference between credit prices faced by low and high risk borrowers is relatively small. In this paper, we do not "solve" this puzzle in the sense of determining why these

[4]This wedge approach was developed in the context of business cycle accounting in Chari et al. (2007).

premia arise; rather, we illustrate the puzzle and seek to measure the impact of borrowing premia on borrower behavior and welfare.[5] Moreover, this pattern holds when controlling for borrowers' income and during both "normal" and "crisis" periods, proxied by the year 2019 and the months of March - June 2020, the outset of the Covid-19 pandemic. Borrowing premia rise across the board in crises, but rise the most for high risk loans.

Second, we develop a quantitative model capable of matching these observed borrowing premia and their dynamics in Section 3. Our economy features competitively priced, defaultable debt as in Chatterjee et al. (2007), and aggregate shocks as in Nakajima and Rios-Rull (2019). We expand on the predominant pricing paradigms in the literature by introducing borrowing premia endogenously into the model using a novel constraint on aggregate loan supply in which "lending standards" serve as the weights on different types of loans. We show that this specification delivers borrowing premia as the product of two components. The first component determines the overall level of premia and varies endogenously with overall credit market tightness.[6] The second component proxies banks' cross-sectional and dynamic loan pricing decisions, which we take as exogenous. Critically, this allows us to disentangle shifts in credit demand from shifts in lending policies using available data.

While an appropriate choice of lending standards in our framework can match any observed joint schedule of borrowing and risk premia, in Section 4 we estimate this model to match the actual schedule of borrowing premia by loan risk constructed in Section 2, as well as other standard credit market moments. We divide our quantitative analysis of this estimated model into two categories, covered in Sections 5 and 6.

Section 5 highlights the cross-sectional and long-run impacts of borrowing premia by comparing the steady state of our baseline model with several variants. Total credit declines by 45% and bankruptcy filings increase by 30% on average compared to an economy with no borrowing premia. The former effect arises because the level of premia increases borrowing costs on average, reducing debt along both the intensive and extensive margins. The latter effect occurs because borrowing premia decline as risk premia increase, flattening loan price schedules and thereby disincentivizing small, low risk loans. Examining the composition of total debt by borrower risk confirms this mechanism: in our baseline model (as in the data), nearly 25% of total credit balances are accounted for by high risk borrowers with default probability of at least 10%. By contrast, this figure is 4.2% for the economy with no premia. A "fixed premium" economy which matches the average level of borrowing premia but not their incidence across borrowers yields similar reductions in overall credit to our baseline, but

[5]We address this important question empirically in an ongoing companion paper, Castro et al. (2020).

[6]A case of particular interest is when this constraint is slack: here we recover the standard pricing relationship from the literature.

lacks this composition effect. Overall, consumption equivalent welfare losses are 0.29 pp on average, sharply left skewed, and especially high for low wealth and low income individuals compared to an economy with no premia.

We consider the impacts of dynamic shifts in lending standards and borrowing premia in Section 6. In Section 6.1 we simulate a negative shock designed to capture the Covid-19 crisis. For this exercise, we re-estimate our lending standards function to match the shift in borrowing premia observed between our base year and the beginning of the crisis period. Then, in Section 6.2 we analyze the full stochastic equilibrium of our model to assess how lending standards and borrowing premia impact business cycles.

Our re-estimation of lending standards delivers two key results. First, we find that the increase in the level of borrowing premia is driven by the tightening of the credit market associated with reduced saving and increased demand for credit in response to the shock. Formally, we estimate that the level of the lending standards function actually decreases on impact, but the endogenous component of borrowing premia rises enough to offset this effect. Second, on impact, standards "rotate" against high risk borrowers, resulting in a relative tightening for these borrowers *on top of* the equilibrium effect due to market tightening. These dynamics are consistent with survey evidence on lending standards and terms of credit from the Senior Loan Officer Opinion Survey (SLOOS). Note that separating these observed shifts in borrowing premia from shifts in lending standards which we cannot observe directly is only possible given the endogenous determination of borrowing premia in the model.

How does this estimated response of standards shape credit outcomes and welfare in response to a negative shock? In our baseline model, debt rises 3.5% less (from its already much lower average level) than in an economy with no premia, and the estimated shift in standards accounts for about half of this response. Standards mostly act on the extensive margin of debt, with the fraction of borrowers increasing 12.0% less when standards do not respond to the negative shock. As in our steady state analysis, premia are quite costly in terms of welfare over the life of the shock, with average losses of 0.35 pp. Notably, our transition dynamics reveal a general equilibrium feedback effect, whereby the return on savings remains relatively high despite the drop in the real interest rate, easing the pressure on the aggregate loan supply constraint. This provides a small but widely-realized boost in welfare in our baseline model relative to a case in which premia are present and responsive to the shock, but specified exogenously: welfare losses double in the latter case. The estimated shifts in borrowing premia also lead bankruptcy filings to increase by 2% more than the case in which standards are fixed, and 20% more than the case with no premia.

Finally, we further expand our analysis and study outcomes over business cycles, revealing a novel effect which highlights the importance of supply frictions. The estimated behavior of borrowing premia implies that interest rate spreads for loans of all risk levels are countercyclical. This new effect is separate from both the standard procyclicality of the equilibrium interest rate and the countercyclicality of average spreads inherited from borrowers' countercyclical earnings risk. The former effect actually helps borrowers by lowering the base price of credit and the latter effect can be diminished by borrowers choosing smaller loans. By contrast, our novel effect negatively impacts all borrowers in a way they cannot circumvent except by staying out of the credit market. This diminishes consumers' ability to insure against risk over the cycle, leading to a 60% rise in the relative volatility of consumption, even in the context of a one-asset model like ours.

1.1 Related literature

Our work contributes to two broad areas of research: (i) quantitative studies of unsecured credit with heterogeneous consumers; and (ii) empirical studies of loan supply frictions. For the first group, our contribution is both empirical and methodological. Empirically, to our knowledge we are the first in the unsecured credit literature to incorporate account-level pricing data from Y-14M into a quantitative model. To understand our methodological contribution, it is useful to think of loan pricing in two stages. First, how do loan size choices and idiosyncratic and aggregate states map into probabilities of default? Second, how do probabilities of default map into loan prices? Our paper focuses on the latter question, while nesting workhorse models in the literature (e.g. Athreya (2002), Livshits et al. (2007, 2010), Chatterjee et al. (2007), and Nakajima and Rios-Rull (2019)) with regards to the former. This allows us to reconcile unsecured credit theory with observed credit prices.[7]

To our knowledge, the closest paper to ours is Nakajima and Rios-Rull (2019), which extends unsecured credit models to an environment with aggregate uncertainty. They find that the countercyclicality of earnings risk and skewness drive the cyclical properties of the credit market, but not enough to generate the observed volatility in unsecured credit. They argue for two possible paths forward: (i) shocks that make credit goods more attractive in expansions; or (ii) shocks that make credit more expensive in recessions across risk levels. Our paper features the latter, since the countercyclicality of borrowing premia make credit more expensive across the board in recessions. Further, our paper supports the idea that constraints in the unsecured consumer credit market have a meaningful impact on aggregate outcomes. For example, Herkenhoff (2019) finds that credit expansions and contractions have contributed to moderately deeper and more protracted recessions over the last 40 years.[8]

[7] Correctly capturing the prices consumers face is critical. For example, Gross and Souleles (2002) find that borrowers' credit card rates are quantitatively important for their borrowing decisions.

[8] Specifically, Herkenhoff (2019) demonstrates that as more individuals obtained credit from 1977 to 2010,

Several recent papers have examined the role of specific pricing and market features to explain key properties and trends in credit markets. For example, Raveendranathan (2020), Herkenhoff and Raveendranathan (2020), and Greenwald et al. (2020) all depart from the standard pricing paradigm and model credit contracts explicitly as long-term credit lines which define a credit limit and an interest rate spread on all borrowing up to that limit. The former two papers yield pricing relationships that are flatter with respect to consumer default risk than most of the literature, consistent with our findings in this paper.[9] In the context of business lending, Greenwald et al. (2020) also makes use of supervisory data from Y-14Q (the business counterpart of Y-14M) and show that credit lines reproduce the flow of credit toward less constrained firms after adverse shocks observed in the data. Another example is Drozd and Kowalik (2019), which uses account-level supervisory data to study the role of promotional pricing. These authors link deleveraging on credit cards during the Financial Crisis in the U.S. to the collapse in promotional activity from late 2008 onward. Our work also provides further insights into the persistence of financial distress (Athreya et al. (2018), Chatterjee et al. (2020)), since the pricing relationships in the model induce persistently larger and higher risk debts for agents who choose to borrow.

Like much of this literature, we use our model to measure the role of unsecured credit in providing consumption insurance for households. Athreya et al. (2009) conduct a similar analysis and conclude that unsecured credit largely does not facilitate consumption smoothing, since riskier types do not get access to cheap credit; Nakajima and Rios-Rull (2019) reach a similar conclusion looking over the business cycle.[10] We reach a similar conclusion, but through a different channel. First, since borrowing premia raise the level of credit for low risk borrowers the way risk premia do for high risk borrowers, the unsecured credit market provides little insurance over most of the risk distribution. Second, since borrowing premia tend to rise during recessions, this effect is compounded over the cycle.[11]

cyclical credit fluctuations affected a larger share of the population and became more important determinants of employment dynamics. While we abstract from modeling interactions with labor supply and labor search decisions, we do find that credit constraints shape the cyclical properties of aggregate consumption.

[9] Herkenhoff and Raveendranathan (2020) also documents the extensive markups in the U.S. credit card industry. Our borrowing premia are consistent with such markups, and we measure how they vary across borrowers.

[10] Arellano (2008) and Chatterjee and Eyigungor (2012) conduct related analyses for sovereign debt.

[11] These findings are in stark contrast to findings that the accumulation of debt and the use of bankruptcy reflect the attempts of households to smooth consumption in response to shocks. Krueger and Perri (2006), for example, document that income inequality increased by 20% over 1972-1998, while consumption inequality increased by only 2% over the same period. These authors argue that larger idiosyncratic shocks after entering the work force drove the rise in income inequality and spurred the growth of credit markets to dampen the transmission of these shocks to consumption. More recently, Aguiar and Bils (2015) find similar results for 1980-2007, although their estimates of consumption inequality matched more closely those of income inequality.

We also contribute to the empirical literature which assesses frictions in loan supply by studying lending standards (e.g. Bassett et al. (2014) at the bank level and Lown and Morgan (2006), Schreft and Owens (1991) in the aggregate). In particular, our paper builds on findings and methods used in Bassett et al. (2014), which constructs a novel credit supply indicator using bank-level responses to the SLOOS on changes in lending standards. In line with our model, they find that tightening of this indicator is associated with a substantial decline in the capacity of business and households to borrow from banks. In related research focused on the Great Recession, Chen et al., (forthcoming) find that uncertainty in macroeconomic outlook rather than banks' balance sheet positions was an important reason why banks tightened standards during the financial crisis.[12] We use our model to assess the impacts of observed changes in lending standards on credit outcomes, but remain silent as to the drivers of these changes. Castro et al. (2020), our companion paper to the current study, fills this gap by combining survey data on banks' changes in lending standards from SLOOS with detailed bank-level and loan-level data on lending from Y-14M and Call Reports to investigate why banks change standards and how they implement these changes.

2 Borrower Risk and Loan Rates in the Data

In this section, we document the relationship between loan rates and borrower risk in the credit card market. We define our borrowing premium measure in Section 2.1, and describe our data set in Section 2.2. In Section 2.3 we report our main empirical results and discuss of how the relationship between borrowing rates and borrower risk differs across incomes and between a period with "normal" lending standards and terms (proxied by 2019) and one with "tightened" standards and terms (proxied by the Covid-19 crisis, March – June 2020).

2.1 Measuring empirical borrowing premia

Standard unsecured credit pricing To fix ideas, we first provide a brief overview of existing workhorse unsecured loan pricing theories.[13] Consider an economy with competitive lenders that offer a variety of contracts to households. Lenders can borrow at the equilibrium interest rate $i(s)$, where s is the aggregate state. A loan contract specifies a size ℓ and a discount price q; the household pays the lender $q \cdot \ell$ today in order to receive ℓ tomorrow. Lenders must choose a mass of contracts of size ℓ to issue to households with individual state x each period, given the current aggregate state s. Next period, households may choose to

[12] These authors build a DSGE model consistent with these findings and find an important role for credit supply shocks in driving cyclical movements of bank lending standards.

[13] See, for example, Athreya (2002); Chatterjee et al. (2007); Livshits et al. (2007).

repay the loan or default. In the case of default, the lender recovers a fraction $\xi \in [0,1]$ of the principal ℓ. This canonical framework delivers the loan pricing equation

$$q(\ell; x, s) = \frac{p(\ell; x, s) + \xi(1 - p(\ell; x, s))}{1 + i(s)}, \text{ where } p(\ell; x, s) = \Pr(\text{repay } \ell \text{ tomorrow} | x, s) \quad (1)$$

is the expected probability of repayment. The key property is that low risk (high p) loans have lower interest rates (higher prices). Expected repayment probabilities fully determine loan prices, which are linear in p with slope governed by ξ and i. In light of this, much of the literature has sought to determine the implications of loan size choices and the evolution of idiosyncratic and aggregate states for default decisions, assuming that prices are determined according to (1).

Comparing model-implied and empirical loan rate spreads How, though, do default probabilities $(1 - p)$ map into loan prices *in the data*? The literature has been silent on this front, and so we attempt to fill this gap using a simple approach. The spread that a borrower pays over the equilibrium interest rate in a standard unsecured credit model – i.e. the one implied by default risk only – may be computed using equation (1):

$$\tilde{R}(\ell; x, s) = \frac{1/q(\ell; x, s)}{1 + i(s)} = \frac{1}{\xi + (1 - \xi)p(\ell; x, s)} \implies \tilde{R}(p) = \frac{1}{\xi + (1 - \xi)p}, \quad (2)$$

where $1/q(\ell; x, s)$ is the gross interest rate on the loan. This representation makes clear that the spread in this class of models depends on individual characteristics only through the repayment probability; that is, p is a "sufficient statistic" for borrower characteristics (x), borrower choices (ℓ), and aggregate conditions (s). For transparency in our empirical approach and parsimony in the model presented in Section 3, we collapse our data set into observations of interest rate spreads and repayment probabilities $(\tilde{R}_{it}, p_{it})$ for each borrower type i in each period t, as well as recovery rates ξ and a benchmark interest rate i_t.[14]

After converting interest rates into spreads, we measure the percentage difference between $\tilde{R}_{it}$ and $\tilde{R}(p_{it})$, and define this as the "borrowing premium," b_{it}

$$b_{it} = \frac{\tilde{R}_{it}}{\tilde{R}(p_{it})} - 1. \quad (3)$$

We view this measure as capturing all additional costs of borrowing in excess of those implied

[14]We measure spreads in ratio terms (as opposed to simple differences) for ease of comparison with the model presented. We describe our measurement of p in the next section. Note, however, that our empirical approach could in principle be generalized to allow borrower choices, borrower states, and the aggregate state to matter separately from their impact on p.

by measurable default risk.[15] These costs arise at least in part from supply frictions, such as lender market power or constraints on loanable funds. We do not attempt to determine the origin of these additional costs in the present paper, but leave this topic for future work. Rather, we measure these costs and construct a model capable of replicating them to assess their impact on the unsecured credit market, consumption, and welfare.

2.2 Data and implementation of measurement approach

To provide evidence on how borrowing premia change with borrower risk, we combine two data sources: (i) Y-14M, a detailed account-level panel data set built from the portfolios of large bank holding companies in the United States, collected by the Federal Reserve Board as part of the Comprehensive Capital Analysis and Review; and (ii) the FRBNY Consumer Credit Panel (Equifax), a nationally representative five percent sample of all credit files for U.S. borrowers. Combining these data sources provides the most complete picture possible of how terms of credit, borrower characteristics, and borrowing and default behavior vary across the universe of borrowers in the U.S. Specifically, this approach allows us to uncover the relationship between borrowing premia on credit card loans and borrowers' probability of default. We now describe the key features of each data set and how we combine them to construct borrowing premia per equation (3).[16]

Y-14M The Y-14M data is collected monthly and includes detailed loan-level data that banks report as part of their annual stress tests. This data is only available starting in 2012 and is restricted to the 35 largest banks, but it includes detailed data on borrower characteristics and loan terms not available in other data sets used in the literature. In particular, we can observe terms of credit (including interest rates and credit limits), as well as measures of both the extensive and intensive margins of credit usage across borrowers by key characteristics, including credit score and income.

Equifax We supplement Y-14M with Equifax because Y-14M, unfortunately, does not contain good measures of default at the borrower level.[17] Equifax contains a rich set of variables describing consumers' credit behavior, including various measures of delinquency

[15] This measurement is similar in approach and interpretation to that presented in Chari et al. (2007).

[16] Focusing on terms of credit set by U.S. banks does not meaningfully limit our analysis. According to the FRB G.19 release, the bank share of total revolving unsecured consumer credit is about 90%. Within the banking sector, both the Y-14M and SLOOS samples (the latter used later in the paper) include the largest issuers of credit card loans and are representative of the U.S. unsecured credit market.

[17] While information about banks' assessment of each account's probability of default is collected in Y-14M, this is an optional reporting item for most banks (except those subject to the "advanced approaches" rule). As a result, the variable is quite sparse, with less than 20% of banks reporting it.

and default and outstanding balances for each type of loan, despite lacking information on income or terms of credit. The data set is structured as a quarterly panel, beginning in 1999, with snapshots of consumers' credit profiles at the end of each quarter. Starting in January 2020, the data is available at monthly frequency.

Combining the data sets To compute average borrowing premia by probability of default, we combine Y-14M and Equifax using measures of borrower credit scores in the two data sets as the common identifier. Note that our procedure does not (and cannot) match individual borrowers or accounts across the two data sets. Instead, we aggregate borrowers into bins and appeal to the extremely large samples in both data sets to match information from each data set at the bin level. We proceed in four steps.

First, we group borrowers in the two data sets by vigintiles (5% bins) of borrower's credit scores in 2019 in each data set.[18] In Equifax, this measure is the Equifax risk score (ranging from 280 to 850) and in Y-14M this measure is the FICO score (ranging from 300 to 850).

Second, using Equifax, we compute the average likelihood of default for each of these 20 groups. Our measure of default includes bankruptcy and severe derogatory.[19] Both bankruptcy and severe derogatory affect ability to access credit and the interest rates on credit card loans, the focus of our estimation procedure. Importantly, both imply that the lender has removed the debt from its books and thus represents the best counterpart to the model definition of default, as opposed to including delinquent loans, even with longer term past due.[20] We truncate the sample to eliminate the highest risk borrowers in the three lowest risk score vigintiles. This keeps consumers with probabilities of default up to 20% in our sample, which we take as a high upper bound for our measure of default and representative of the economic behavior our model captures. This truncated sample covers more than 90% of credit card balances.

Third, using Y-14M, we compute average interest rates conditional on the median level of debt for the 20 borrower risk groups.[21] We control for debt level in order to neutralize the

[18]Our results are robust to finer partitions, for example into 2% bins.

[19]"Severe derogatory" refers to any delinquency paired with a repossession, foreclosure, or charge-off.

[20]Our data contain additional information for account payment or delinquency status, including, in order of severity: current; 30 days past due (DPD); 60 DPD; 90 DPD; 120+ DPD; in collections; severe derogatory; and bankruptcy. For robustness, we use a broader definition which also includes 120+ DPD in addition to severe derogatory and bankruptcy, as well as a narrower definition which only includes bankruptcy. The patterns we find are the same with only slight differences in the levels. For further details see the right panel of Figure B.1 in the Appendix. In principle, one could construct the same exact narrow definition of default using the bankruptcy flag variable in Y14M data or the broader definition using information on days past due. However, severe derogatory, the key variable used in our preferred definition of default that matches our model's definition, is not reported in Y14M.

[21]We proxy the median with the third quintile of debt to include more observations. For robustness, we compute interest rates controlling for smaller debt levels with more borrowing: patterns look similar.

effects of loan size choices in the pricing of loans. This is an economically important step for consistency between our model and the data.[22] We transform interest rates into borrowing premia using an average prime rate (data analog of $i(s)$) of 5.16% for 2019.

Fourth, we map borrowing premia from Y-14M to likelihood of default from Equifax. This collapses borrower credit scores observed in Y-14M to default probability. This mapping supposes two underlying assumptions. First, the population of borrowers in the two data sets is the same. Given the dominance of the largest banks in the credit card market, almost the entire universe of credit card loans and borrowers (as represented by Equifax) are captured in the Y-14M data, and so we view this assumption as reasonable. Second, the two measures of credit score (risk score in Equifax and FICO score in Y-14M) are equivalent in assessing borrower's likelihood of default.[23]

2.3 Results: borrowing premia by default risk and over time

This section presents our main findings regarding variation in borrowing premia across default risk and over time. We use 2019 as our base year ("normal" lending standards) and then recompute borrowing premia for March through June 2020 ("tightened" standards, due to Covid-19).[24] We keep the probability of default and credit score matching the same across the two periods.[25] For the latter period, we use a prime rate of 3.18% to convert interest rates into spreads for the calculation of borrowing premia, reflecting the sharp reduction in the policy rate at the outset of the pandemic.

Figure 1 documents the stark divergence between interest rate spreads observed in our combined Y-14M and Equifax data sets and those implied by workhorse unsecured credit models. As default probability increases, loan rates increase in both settings, but this rise is far steeper in the literature than in the data. In particular, Figure 2 shows that the average

[22] Credit card contracts in the data take the form of credit lines, as opposed to a full loan-specific rate schedules. For excellent examples of quantitative models using the credit line paradigm, see Raveendranathan (2020) and Herkenhoff and Raveendranathan (2020).

[23] Given that multiple scoring models are used in determining applicant's creditworthiness, one might argue that the algorithm used to compute different credit scores might not produce identical measures for the same consumer. However, findings in a 2012 CFPB report reveal that the scores produced by different models provide similar information about conumers' relative creditworthiness. Additionally, authors' calculations using the Credit Risk Insight Servicing/McDash (CRISM) data reveal that the correlation between the two scores is very high (about 0.9), further supporting this assumption in the context of mortgage lending. Results are available upon request.

[24] To be sure, the Covid crisis continues beyond June 2020. However, we use the early period March-June to capture the immediate impact of the virus on bank lending standards. In the SLOOS, almost all banks reported tightening standards in this period, whereas only 15% of banks reported further tightening standards over July-September.

[25] Figure B.1 shows that the distribution of default probabilities and credit scores is stable between these periods.

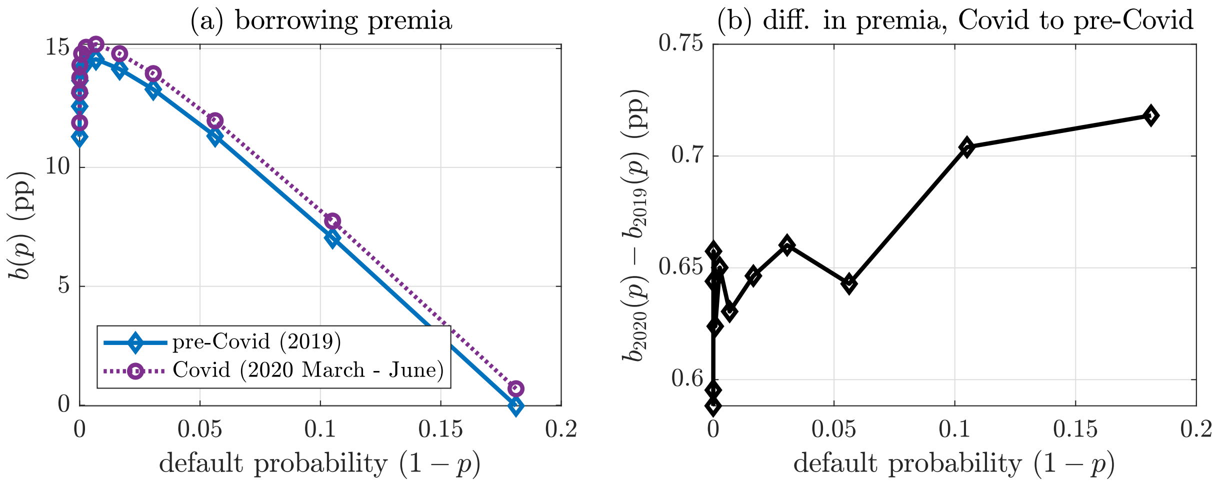

Figure 2: **Borrowing premia by default probability**

Notes: This figure is constructed using the combined Equifax and Y-14M sample described in section 2.2, with $b(p)$ defined in (3). "Covid" refers to March-June 2020; pre-Covid refers to the full year of 2019.

interest rate spread on a virtually riskless loan in the data ranges from 11 to 14 percentage points (pp), whereas standard theory would predict no spread.[26] This confirms the presence of large borrowing premia in this market. The left panel of Figure 2 presents these borrowing premia directly for the pre-Covid period (2019, blue line) and the Covid period (March-June 2020, purple line); the right panel plots the difference between the two periods. These findings have important implications both in the cross-section and over time.[27]

Cross-section We stress two primary implications of our results in Figure 2. First, there is a wedge between the return on savings and the cost of borrowing even for risk-free loans. This clearly distorts the *extensive* margin of debt usage, since there is a discrete shift in the return on savings and the rate on even a vanishingly small loan. Second, borrowing premia

[26]Of course, one could include some fixed borrowing or intermediation premium in the loan price schedule. This case, which we consider later, which still cannot replicate the flatness of the spread schedule we observe.

[27]In our analysis we use the interest rate from Y14M data given that the richness of the micro-data allows us to study variation across individuals, including risk and income, as well as over variation over time. The average rate we obtain for our base year, 19.4 percent, is slightly higher compared to the one in the G19 FRB credit release for the same year, of 17 percent. While G19 is the most frequently used data to guide models of unsecured credit, the data are aggregated at the bank level and thus do not allow for detailed cross-sectional analysis. Even so, the dynamics of the two data series compare well for the period where data are available from both sources. Additionally, we use the statutory rate, as opposed to computing an effective rate from Y14M, given that the retail APR represents a better measure for issuer pricing strategies. While levels between statutory and effective rates are slightly different, the patterns across borrower risk are the same. See, for example, the 2019 CFPB Report on The Consumer Credit Card Market. In fact, our finding that rates flatten quite a lot for the high probability of default which holds across effective and statutory rate measures, suggests that non-price terms seem to drive that portion of the market, justifying our censoring of the data below the 4th credit score vigintile. Of course, the interaction between price and non-price terms is important, but is it outside of the scope of this paper.

are both non-monotone and non-linear in default probability. This distorts the *intensive* margin of debt usage, since the pricing penalty associated with choosing a higher risk loan appears to be much smaller in the data than in standard models. Borrowing premia dissipate as risk premia increase.

Dynamics Comparing across periods reveals that borrowing premia rose in 2020 across all levels of risk, and rose most for relatively high risk loans. At the outset of the Covid-19 pandemic, lenders reported significantly tightening lending standards and terms in the consumer credit market. More generally, banks tend to tighten (loosen) lending standards and terms in economic downturns (expansions).[28] In line with these dynamics for lending standards, banks also tend to tighten terms of credit – both limits and spreads – during recessions and ease terms during expansions (see Figure 9). A critical question plaguing empirical studies of lending standards is: what exactly are lending standards and how are they reflected in the unsecured credit market? Our analysis suggests that increases in borrowing premia could be considered a direct result of tightening lending standards.[29]

The right panel of Figure 2 illustrates how borrowing premia change in the crisis period relative to 2019. While borrowers at each level of risk face tighter terms of credit (higher borrowing premia), these changes are not uniform across borrower risk levels. Higher risk borrowers see larger increases in borrowing premia, with by far the largest changes observed for our highest risk borrowers. This is in line with survey evidence that shows that when banks tighten standards, they tighten them more for higher risk borrowers (see Figure B.5a and discussion in Section 4.3). We conclude that while the relationship between borrowing premia and risk remains qualitatively the same during normal and crisis periods, there is an important quantitative difference, particularly for high risk borrowers.

[28] For example, the net fraction of banks that tightened standards on credit card loans over the first quarter (January-March), as reported in the April SLOOS was 92.6 percent and over the second quarter (April-June), as reported in the July SLOOS was 99.75 percent, the highest in the history of the series. These fractions are based on responses that have been weighted by each bank's outstanding credit card loans in their loan portfolios. Overall, almost all large banks reported tightening and majority of small banks did so over the first part of 2020. In their written comments, banks indicated that the tightening reported over the first quarter was mainly due to tightening in March, driven by the COVID-19 pandemic. Details about how these fractions are computed are provided in the Appendix. In addition, 94 percent of banks reported tightening standards on credit card loans, on net, during the Global Financial Crisis, while 14.5 net fraction of banks reported easing standards during the expansion period between June 2010 and June 2016.

[29] Of course, there could be other direct implications of tightened standards, including increases in minimum credit score requirements for credit approval or decreases in credit limits conditional on getting a loan. In laying out a flexible framework suitable for this type of analysis, our paper represents a first step in allowing for these interpretations and can serve as theoretical foundation for further analysis in this direction.

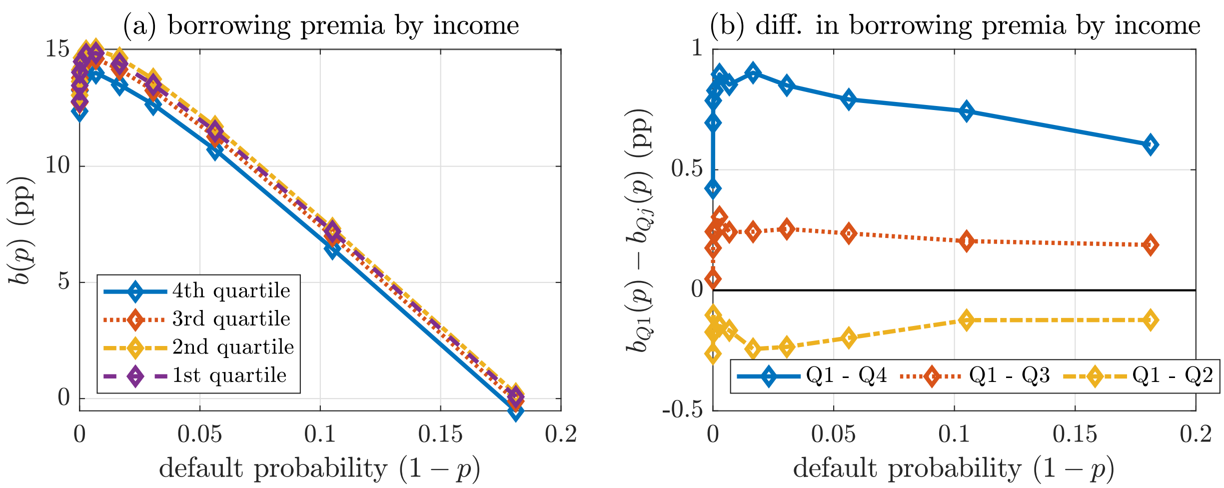

Figure 3: **Borrowing premia by default probability across income quartiles**

Notes: This figure is constructed using the combined Equifax and Y-14M sample described in section 2.2, with $b(p)$ defined in (3).. "Income" refers to "income at origination" in Y-14M. In the right panel, all differences are computed with respect to the first income quartile (purple line in the left panel).

Is p enough? Variation in borrowing premia by income A crucial assumption in our measurement approach is that default risk is summarized completely by credit score. Is this assumption valid? We address this question directly by measuring borrowing premia for risk score vigintile as above, but controlling in addition for borrowers income quartile.[30]

As shown in panel (a) of Figure 3, the patterns discussed previously are preserved across income quartiles. Top earners face lower borrowing premia relative to bottom earners across the default probability distribution, but the elasticity of borrowing premia with respect to default probability appears to be an order of magnitude higher than the elasticity with respect to income. While variation in borrowing premia across borrower risk are large for all income groups, differences in premia between borrowers with different income levels but the same risk score are quite small. Panel (b) of Figure 3 shows that the differences in premia in the top three quartiles relative to those with earnings in the bottom quartile are below 1 pp. In contrast, the difference between low risk and high risk borrowers is approximately 15 percentage points. These findings imply that default probability or borrowers' risk score are the most important determinant when pricing credit card loans.

[30]We limit history to loans originated in pre-crisis years (2005). We choose 2005 so as to cover a sufficiently large share of observations but also include high quality income data. Y-14M also collects monthly updated information on income, but this variable is optional and poorly populated. Unlike interest rates and other terms of credit which are reported by banks, income is self-reported in Y-14M. We provide details on this in the Appendix.

Summary This evidence points to supply frictions in the unsecured credit market which the literature has not yet addressed. Specifically, borrowing premia are large on average but dissipate with borrower risk. Furthermore, borrowing premia increase across levels of borrower risk during a downturn. The model we build in Section 3 is designed to reconcile existing theory with this evidence through the lens of lending standards, delivering empirically consistent terms for consumer credit. Given the shifts in borrowing premia across periods, supply frictions in the model must be re-estimated to account for differences in standards and terms between different states of the economy.

3 Model of Unsecured Credit with Lending Standards

The model adapts Chatterjee et al. (2007) to include aggregate shocks, in the spirit of Nakajima and Rios-Rull (2019). The key innovation in the model is to tractably model consumer credit supply in a way that allows the model to match empirically observed interest rates by probability of default. The model features an upper bound on the fraction of aggregate savings which can be allocated away from productive capital into loans to individuals to be used to smooth consumption. The multiplier on this constraint implies a wedge between the return on savings and the cost of borrowing, which comprises the endogenous component of the borrowing premia discussed in our empirical analysis. Moreover, since loans of different risk levels bear different weights in our specification of this constraint, different loans in general have different borrowing premia.

Time is discrete, and there are three types of agents. First, there is a unit mass of infinitely lived households who decide each period how much to consume, how much to borrow or save in a single asset, and whether or not to default on existing debt. Second, there is a representative firm which produces according to a constant returns to scale production function and hires capital and labor in competitive factor markets. Third, there is a representative, competitive lender who offers menus of borrowing and saving contracts to households. The prices offered in these contracts are affected by borrowers' idiosyncratic states, their choices, and the aggregate state of the economy.

3.1 Legal environment and bankruptcy

Following Chatterjee et al. (2007) and Nakajima and Rios-Rull (2019), the bankruptcy procedure in the model captures the Chapter 7 bankruptcy procedure in the U.S. A household's credit history is summarized by a "bankruptcy flag" $f \in \{0, 1\}$. A status of $f = 1$ ($f = 0$) indicates the presence (lack of) a default in the household's recent credit history. A household without a bankruptcy flag has access to the credit market (i.e. may choose to borrow, choosing wealth tomorrow $a' < 0$); a household with a bankruptcy flag cannot borrow (i.e. must choose $a' \geq 0$).

A household with debt must choose whether to file for bankruptcy ($d = 1$) or pay back ($d = 0$). In the event of a bankruptcy, the household:

1. cannot borrow or save in the current period ($a' = 0$);
2. begins the next period with a bankruptcy flag, $f' = 1$;
3. incurs a fixed cost equal to the minimum of the fixed filing cost $\kappa > 0$ or 25% of current labor earnings;[31]
4. incurs a non-pecuniary utility cost ("stigma") $\chi > 0$; and
5. pays back only a fraction $\xi \in [0, 1]$ of its total debt.

A household with a bankruptcy flag loses the flag and regains access to the credit market with i.i.d. probability $\theta \in [0, 1]$, yielding an average duration of bad credit standing of $1/\theta$.

The institution of bankruptcy implies that competitive, profit-maximizing lenders must price loans today to reflect the probability of default tomorrow. In the case of default, we assume that lenders receive the fraction ξ of the loan that is repaid. Including this partial recovery is important for consistency with the data, since empirically a bankrupt or severely derogatory account does not imply a zero return for the lender.

3.2 Household preferences

Households are risk averse and value consumption flows according to the utility function $u(c) = \frac{c^{1-\gamma}-1}{1-\gamma}$, where $\gamma > 1$ is the coefficient of relative risk aversion. Since this function includes no leisure, households supply their full labor productivity inelastically in the model. Additionally, households discount the future by a discount factor $\beta \in (0, 1)$. Individuals' time preferences are stochastic and evolve according to a Markov process $\Gamma^{\beta}(\beta'|\beta)$.

Furthermore, households receive a pair of additively separable shocks, $\nu = \{\nu^D, \nu^{ND}\}$, attached to the decision to default or not default. These shocks are independent and identically distributed across individuals and time and follow a type one extreme value distribution with scale parameter $\zeta > 0$. These shocks serve three purposes. First, they imply a strictly

[31] We assume throughout that this cost is a deadweight loss associated with default. An alternative (or complementary) assumption is that κ represents a garnishment of earnings used to partially repay lenders in the event of default. The capping of default or bankruptcy filing costs at 25% of current labor income is consistent with current U.S. bankruptcy law's restrictions on earnings garnishment.

positive probability of default on even the safest loans, consistent with the data. Second, they smooth out individuals' probability of repayment and therefore loan price schedules, which facilitates convergence of the model solution as described below. Third, they capture the fact that many defaults are associated not with income shocks, but events such as marital disruptions and medical expenses, which we do not model explicitly.

3.3 Technologies

Production There is a single good used for consumption and investment, and all quantities are measured in real terms. The good is produced by the firm according to the constant returns production function $F(K, N; z) = zK^{\alpha}N^{1-\alpha}$, where: K is aggregate capital; N is aggregate labor supply (in effective units); z is total factor productivity (TFP), which has transition process $\Gamma^z(z'|z)$; and $\alpha \in (0, 1)$ is a parameter measuring the capital share in production. Since there are no government expenditures, all production must be channeled toward: aggregate consumption, C; aggregate investment, $I = K' - (1-\delta)K$, where $\delta \in [0, 1]$ is the depreciation rate on capital; or aggregate default costs.

Lending The model's main innovation is the incorporation of lending standards. Motivated by our empirical findings, we model lending standards using a single constraint on aggregate loan supply. The function $\lambda(p; z)$ denotes the weight a loan with repayment probability p (described below) receives in this constraint when TFP is z. This function varies with p so that borrowing premia vary with loan risk, and with z so that these premia vary over time. This constraint dictates the maximum fraction of savings in the current period that lenders can allocate to loans to households: that is,

$$\text{total } \lambda\text{-weighted funds borrowed today} \;\leq\; \text{total funds saved today} \tag{4}$$

This specification delivers a multiplier in the lender's problem which drives an endogenous wedge between the cost of borrowing and the returns on savings. Since the weight on a loan of a given riskiness varies across both risk levels and time according to the $\lambda(\cdot)$ function, borrowing premia also vary in this way. Equation (17) below adapts (4) into formal notation.

3.4 Endowments and state vectors

Households begin the period with net worth $a \in \mathbb{R}$. Each household has labor productivity $\epsilon_1\epsilon_2\epsilon_3$, comprised of three components. The first, $\epsilon_1 \in \mathbb{R}_+$, is a permanent earnings type; the second, $\epsilon_2 \in \mathbb{R}_+$, is a persistent earnings component which follows an AR(1) process with persistence ρ_{ϵ_2} whose variance $\sigma_{\epsilon_2}(z)$ depends on the exogenous aggregate state; and the third, $\epsilon_3 \in \mathbb{R}_+$, is a transitory component. We denote the generalized transition process over labor productivity by $\Gamma^{\epsilon}(\epsilon'|\epsilon, z')$.[32] The full idiosyncratic state of the household is $x = (a, \beta, f, \epsilon = (\epsilon_1, \epsilon_2, \epsilon_3), \nu)$, and the endogenous distribution of households over x in the current period is denoted by $\mu(x)$. In this setting, the aggregate state of the economy is $s = (z, \mu(x))$. All agents take this aggregate state and its law of motion as given.

3.5 Market arrangements

Factor markets The rental rate on capital r and the wage rate w are determined competitively. Firms solve a static problem, delivering standard factor prices:

$$w = z\alpha \left(\frac{K}{N}\right)^{\alpha-1} \tag{5}$$

$$r = z(1-\alpha)\left(\frac{K}{N}\right)^{\alpha} \tag{6}$$

Lending Lenders are competitive and offer a variety of contracts to households to maximize expected profits. A contract specifies a size ℓ and a discount price q, whereby the HH pays the lender $q \cdot \ell$ today in order to receive ℓ tomorrow. The appropriate sign convention thus defines contracts with $\ell < 0$ as loans and those with $\ell > 0$ as savings. In the current period (state s), lenders must choose a mass of contracts, $m'(\ell; x, s)$, of size ℓ to issue to households with state x. Lenders can borrow at the equilibrium risk-free interest rate i. Lenders are fully diversified against individual risk given the assumption of a continuum of households, but in the presence of aggregate shocks lenders may realize profits or losses ex post despite receiving zero profits in expectation. Since these ex post profits and losses are negligible quantitatively, we assume that these profits and losses are dissipated to an unmodeled external sector through net borrowing at the equilibrium interest rate.[33]

3.6 Households' decision problem

Good credit standing A household in good credit standing ($f = 0$) first decides whether or not to default:

[32] This earnings process is tailored to accommodate the implementation of Storesletten et al. (2004), but of course is quite general and may be extended to other processes.

[33] Given this one-asset market structure, one may consider lenders as "choosing" aggregate capital for the next period, K', in a manner consistent with households' saving and borrowing behavior. This structure extends the canonical setting of Chatterjee et al. (2007), which delivers the standard break-even default pricing widely used in the consumer bankruptcy literature. As shown in section 3.7, it is desirable to formulate the full dynamic optimization of the lender in this setting in order to map out the effects of our aggregate loan supply constraint (4).

$$V_0(a,\beta,\epsilon,\nu;s) = \max\left\{V_0^D(a,\beta,\epsilon;s)+\nu^D, V_0^{ND}(a,\beta,\epsilon;s)+\nu^{ND}\right\}, \tag{7}$$

where V_0^D and V_0^{ND} are the "fundamental" values associated with defaulting and not defaulting, and ν^D and ν^{ND} are preference shocks. Of course, default is only feasible if $a < 0$. The fundamental values are, respectively,

$$\begin{aligned} V_0^D(a,\beta,\epsilon;s) &= u\left(\xi a + \max\left\{w\epsilon_1\epsilon_2\epsilon_3 - \kappa, 0.75\times w\epsilon_1\epsilon_2\epsilon_3\right\}\right) \\ &\quad -\chi + \beta\mathbb{E}\left[V_1(0,\beta',\epsilon';s')\right] \qquad (8) \\ V_0^{ND}(a,\beta,\epsilon;s) &= \max_{a'\in\mathcal{F}_0(\beta,a,\epsilon;s)} u\left(c(a';\beta,\epsilon,s)\right) + \beta\mathbb{E}\left[V_0(a',\beta',\epsilon',\nu';s')\right] \qquad (9) \end{aligned}$$

The default value (8) reflects the fact that a defaulting household can neither borrow nor save, incurs a default cost, loses good credit standing, and must still pay back a fraction ξ of the loan. The value of not defaulting (9) reflects the fact that the HH can either borrow or save, choosing $a' \in \mathcal{F}_0(a,\beta,\epsilon;s)$, the set of feasible choices:

$$\mathcal{F}_0(a,\beta,\epsilon;s) = \left\{a' \in \mathcal{A} :\ c(a';a,\beta,\epsilon,s) \geq 0\right\},$$

where the consumption associated with each action depends on its equilibrium price:

$$c(a';a,\beta,\epsilon,s) = \begin{cases} a + w\epsilon_1\epsilon_2\epsilon_3 - q(a';\beta,\epsilon,s)a' & \text{if } a' < 0 \\ a + w\epsilon_1\epsilon_2\epsilon_3 - \overline{q}(s)a' & \text{if } a' \geq 0 \end{cases} \tag{10}$$

Observe that the price of a loan, $q(a';a,\beta,\epsilon,s)$, depends on the household state, the aggregate state, and the loan size, while the price of a savings contract depends only on the aggregate state, $\overline{q}(s)$. This will be derived directly from the lenders' problem.

Since ν follows a type one extreme value distribution,[34] the probability of default is

$$g_d(a,\beta,\epsilon;s) = \begin{cases} 0 & \text{if } a \geq 0 \\ \left[1 + \exp\left\{\frac{V_0^{ND}(a,\beta,\epsilon;s) - V_0^D(\beta,\epsilon;s)}{\zeta}\right\}\right]^{-1} & \text{if } a \leq 0 \end{cases} \tag{11}$$

[34] These results are standard in discrete choice, e.g. McFadden (1973), Train (2009). For recent applications to macroeconomic models with default, see Chatterjee et al. (2020); Dvorkin et al. (2019).

The same analysis shows that the expected value of being in good credit standing is

$$
\begin{aligned}
\overline{V}_0(a,\beta,\epsilon;s) &= \int_{\mathcal{V}} V_0(a,\beta,\epsilon,\nu;s)dF(\nu) \\
&= \zeta\gamma_E + \zeta\log\left[\mathbf{1}[a<0]\exp\left\{\frac{V_0^D(\beta,\epsilon;s)}{\zeta}\right\} + \exp\left\{\frac{V_0^{ND}(a,\beta,\epsilon;s)}{\zeta}\right\}\right],
\end{aligned}
$$

where γ_E is the Euler-Mascheroni constant.

Bad credit standing A household in bad credit standing ($f = 1$) can neither default nor borrow. Therefore, such a household decides only how much to save:

$$
\begin{aligned}
V_1(a,\beta,\epsilon;s) &= \max_{a'\in\mathcal{F}_1(\beta,a,\epsilon,\xi;s)} u(c(a';a,\beta,\epsilon,s)) \\
&\quad +\beta\mathbb{E}\left[(1-\theta)V_1(a',\beta',\epsilon';s') + \theta V_0(a',\beta',\epsilon';s')\right]
\end{aligned}
\tag{12}
$$

The feasibile set reflects the fact that borrowing is forbidden, and so

$$
\mathcal{F}_1(a,\beta,\epsilon;s) = \{a' \in \mathcal{A} | c(a';a,\beta,\epsilon,s) \geq 0, a' \geq 0\},
$$

with $c(a';a,\beta,\epsilon,s)$ given by the bottom expression in (10). The optimal savings policy is denoted by $g_a(x;s)$.

Law of motion for distribution of households The process for TFP is exogenous, but the distribution of households over idiosyncratic states is endogenous. In order to properly take the expectations in equations (8), (9), and (12), households must know the law of motion for the aggregate distribution, denoted by:

$$
\mu' = \Delta(\mu, z, z'). \tag{13}
$$

Following the literature, in our numerical solution households approximate (13). In a deterministic steady state, the distribution $\mu(x)$ is a stationary fixed point of this operator.

3.7 Loan and savings pricing

The lender maximizes expected discounted flow profits subject to the aggregate loan supply constraint. Flow profits for a lender are the sum of net capital returns and repayments on old contracts, net of issuances for new contracts:[35]

$$\pi = \underbrace{(1+r-\delta)K - K'}_{\text{net return on capital}} + \underbrace{\sum_{x,\ell} q(\ell;x,s)m'(\ell;x,s)\ell}_{\text{issuances, new contracts}}$$
$$- \underbrace{\sum_{x_{-1},x,\ell} (1-g_d(\ell;x,s)+\xi g_d(\ell;x,s))\, m(\ell;x_{-1},s_{-1})\ell \Pr(x|x_{-1};z)}_{\text{repayments, last period contracts}} \tag{14}$$

The first term is the return on aggregate capital (rK), net of investment ($K' - (1-\delta)K$). The second term reflects issuances of new contracts $\mathcal{M}' \equiv \{m'(\ell;x,s)\}$, which have discount price $q(\ell;x,s)$. The third term reflects repayments on last period's contracts, $\mathcal{M} \equiv \{m(\ell;x_{-1},s_{-1})\}$. The $g_d(\cdot)$ term in this expression accounts for defaults on loans made in the previous period, while the $\Pr(x|x_{-1};z)$ accounts for exogenous transitions of individual states between the last period and the current one. Going forward, it is useful to define $p(\ell;x,s)$, the expected probability that a loan of size ℓ made to a borrower in state x under aggregate state s will be repaid tomorrow. Since savings contracts have no notion of default, $p(\ell;x,s) = 1$ for all $\ell \geq 0$. For loans, however,

$$p(\ell;\beta,\epsilon,s) = \int_{\mathcal{B}\times\mathcal{E}\times\mathcal{S}} [1 - g_d(\ell,\beta',\epsilon';s')]\, \Gamma^{\beta}(d\beta'|\beta)\Gamma^{\epsilon}(d\epsilon'|\epsilon,z')\Gamma^{z}(dz'|z). \tag{15}$$

The lender problem may be written recursively as

$$W(K,\mathcal{M};s) = \max_{K',\mathcal{M}'} \pi(K',\mathcal{M}';s,K,\mathcal{M}) + \frac{1}{1+i(s)}\mathbb{E}_{s'|s}\left[W(K',\mathcal{M}';s')\right] \tag{16}$$

$$\text{subject to} \quad -\int_{\mathcal{B}\times\mathcal{E}} \lambda(p(\ell;x,s);s)q(\ell;x,s)\ell\mathbf{1}[\ell<0]dm'(\ell;x,s) \tag{17}$$
$$\leq \int_{\mathcal{B}\times\mathcal{E}} q(\ell;x,s)\ell\mathbf{1}[\ell\geq 0]dm'(\ell;x,s)$$

The objective function (16) is the recursive formulation of the discounted sum of the flow profits defined in (14), where the lenders' discount factor is the equilibrium interest rate. The expectation operator in this expression explicitly reflects the lender taking as given the equilibrium law of motion for the household distribution.

The key addition in our model is constraint (17), which implements the generic constraint (4). The summation on both sides is over all idiosyncratic states, but the summation on the

[35]Repayments on yesterday's savings contracts reduce current bank profits, while issuances of new loan contracts reduce current bank profits. In steady state, as in Chatterjee et al. (2007), $\pi = 0$ always. With aggregate shocks, however, it is possible that there will be unanticipated positive or negative profits. Our formulation assumes that lenders can lend (borrow) any windfall (shortfall) at the equilibrium interest rate i. Quantitatively, these excess profits or losses are negligible.

left (right) side of the equation is only over loans (savings).

Analyzing this problem using standard techniques and placing a multiplier $\eta \geq 0$ on constraint (17) delivers the set of pricing equations[36]

$$
\begin{aligned}
i(s) &= \mathbb{E}_{s'|s}\left[r(s')\right] - \delta & (18)\\
q(\ell; x, s) = \overline{q}(s) &\equiv \frac{1}{(1+i(s))(1+\eta(s))} \text{ if } \ell > 0 & (19)\\
q(\ell; x, s) &= \frac{\xi + (1-\xi)p(\ell; x, s)}{(1+i(s))\left(1+\eta(s)\lambda(p(\ell; x, s); z)\right)} \text{ if } \ell < 0 & (20)
\end{aligned}
$$

Equation (18) is effectively a "no-arbitrage" condition which comes from the optimality condition for K' and is unaffected by the loan supply constraint. Equation (19) defines the common price on all savings contracts, $\overline{q}(s)$. Since there is no default risk, individual states x do not affect this price, but the tightness of the loan supply constraint and the interest rate do. If the constraint binds so that $\eta > 0$, then $\overline{q}(s) < (1+i)^{-1}$ and savers earn a premium, easing the constraint by promoting savings among households. Equation (20) is the price of a loan. The numerator is the expected repayment per unit of principal (adjusting for default risk and recovery given default), and the denominator reflects that borrowers pay an additional premium above and beyond the base cost of funds adjusted for expected repayment. As with savers, when the constraint is tighter, the response of the multiplier η eases the constraint by raising loan rates to discourage borrowing on the margin. This effect is more pronounced for loans which have high λ-weights in constraint (17).

3.8 Equilibrium

A recursive competitive equilibrium in this model is a list of: (i) value functions $V(x; s)$ for households, with associated default and savings policies $g_d(x; s)$ and $g_a(x; s)$; (ii) factor prices $r(s)$ and $w(s)$; (iii) credit prices $i(s)$, $\overline{q}(s)$, and $\eta(s)$; (iv) loan price schedules $q(\ell; x, s)$; (v) aggregate factor supplies $N(s)$ and $K(s)$; and (vi) a law of motion Δ such that

1. **Households optimize:** $V(\cdot)$ and the associated optimal policies are consistent with equations (7) through (12);

2. **Firms optimize:** factor prices satisfy (5) and (6);

3. **Lenders optimize:** $i(s)$ satisfies (18), $\overline{q}(s)$ satisfies (19), and $q(\ell; x, s)$ satisfies (20);

4. **Consistency:** the law of motion (13) is consistent with households' optimization; and

[36] Details and derivations may be found in Appendix A.1.

5. **Markets clear:**

   (a) labor: $N(s) = \int \epsilon_1\epsilon_2\epsilon_3\mu(dx)$ for all s;

   (b) capital: $K(s) = \int a\mu(dx)$ for all s;

   (c) goods: $C(s) + K'(s) - (1-\delta)K(s) + \kappa \int g_d(x;s)d\mu(x) = zK(s)^\alpha N(s)^{1-\alpha}$ for all s;

   (d) bonds: $m'(\ell;x,s) = \int \mathbf{1}[\ell = g_a(x;s)]\mu(dx)$ for all s

3.9 An illustration of pricing and borrowing premia in the model

As discussed above, it is useful to think of credit pricing in our model in two stages. First, how do loan size choices and the evolution of idiosyncratic and aggregate states map into probabilities of default? Second, how do probabilities of default map into loan prices? Our paper's contribution rests on the latter question, while nesting workhorse models in the literature with regards to the former. Unlike existing models, ours delivers a flexible specification of the elasticity of the loan price with respect to repayment probability. This section illustrates this feature of the model in Figure 4 under a numerical example, and assesses how our model delivers borrowing premia of the sort documented in Section 2.

Loan and savings prices The convention in the literature is to examine price schedules for a specific individual over loan sizes as in panel (b) of Figure 4. To highlight our contribution, we collapse loan prices as a function of repayment probability $p = p(\ell;x,s)$ (or, equivalently, default probability $1-p$) in panel (a) of the figure, since equation (20) highlights that other state variables only affect the price insofar as they affect p. This allows us to depict the mapping of default probabilities into prices across all borrowers at once, rather than the mapping of loan sizes into loan prices for a single borrower.

The yellow dashed lines represent the standard relationship in the literature. As default probability increases, the loan price decreases linearly with a slope equal to the inverse of the (gross) real interest rate, adjusted for recovery. The solid blue line corresponds to our model and has several noteworthy features. First, it generates wedges between the return on savings, the equilibrium interest rate, and the cost of borrowing even for risk-free loans. Second, the relationship between price and repayment probability is non-linear; indeed, any shape can be generated to match the data by an appropriate choice of functional form for $\lambda(\cdot)$. Third, the borrowing premium (defined below) may vary with the riskiness of the loan.

Borrowing premia Our model provides a natural analog to the borrowing premium measure constructed in equation (3) by replacing the empirical interest rate spread with the

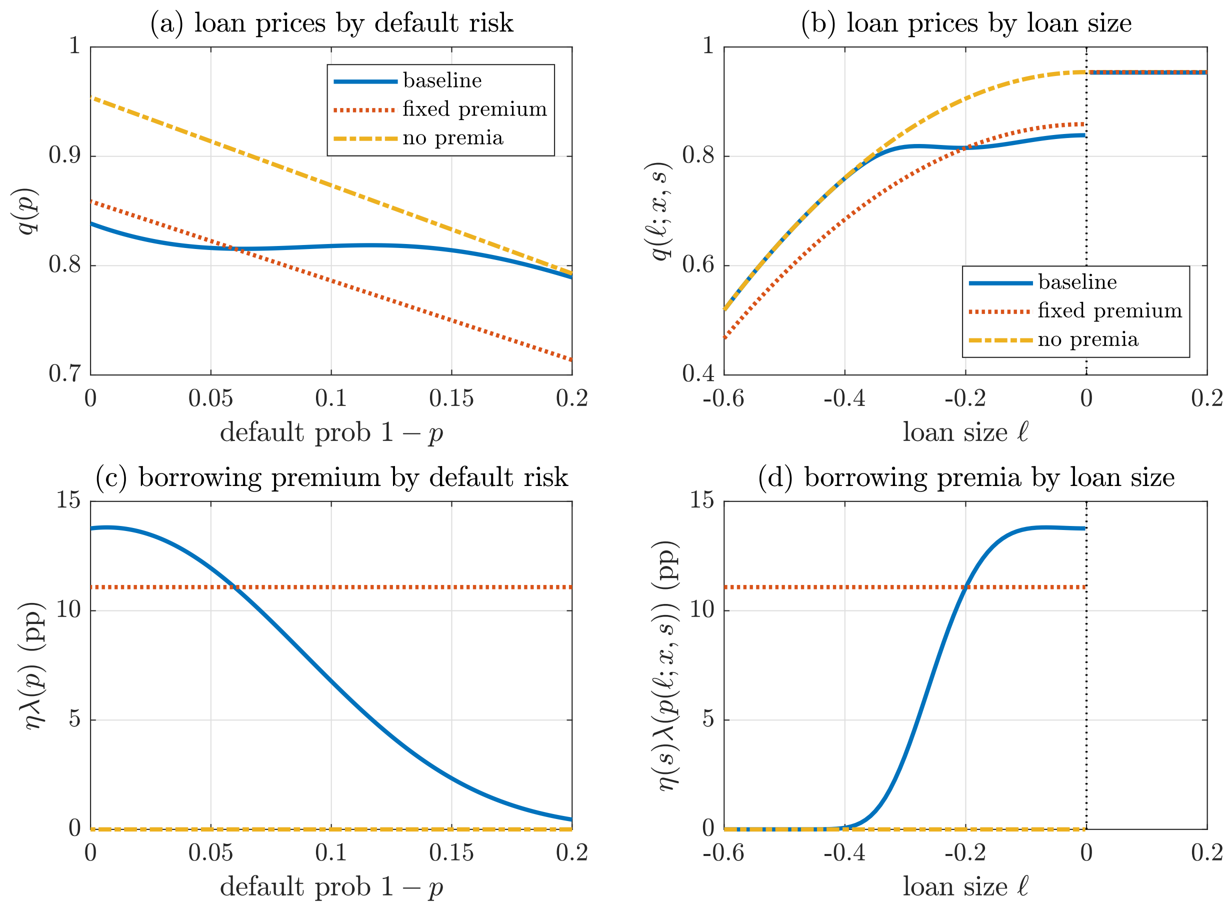

Figure 4: **An illustration of price schedules in the model**

interest rate spread implied by our model. Specifically, denoting by $\hat{R}$ and $\tilde{R}$ the interest rate spreads in our model and in a version of the model with $\lambda = 0$, respectively, we have

$$b(p; s) = \frac{\hat{R}(p; s)}{\tilde{R}(p; s)} - 1 = \eta(s)\lambda(p; s) \tag{21}$$

Equation (21) cleanly highlights the two components of borrowing premia in our model. First, borrowing premia endogenously increase across all levels of risk when the loan supply constraint binds more tightly. This implies that as the supply of savings decreases, or the demand for loans increases, borrowing premia increase and reduce the demand for credit. Second, the shape of the borrowing premium schedule with respect to default probability is entirely determined by the exogenously specified $\lambda(\cdot)$ function. In this example (panel (c), as in the data), the lending standards function has been chosen to create a hump-shaped profile of borrowing premia, with the highest levels borne by the lowest risk loans. Panel

(d) translates this into loan size space for a given borrower. Clearly, the borrowing premia combine with default risk premia to generate a much flatter profile of loan rates, the key gap with respect to the data that we have tried to fill with our model.

An alternative: fixed premium Some models in the literature incorporate a simple fixed borrowing premium. Loan prices in such an economy are given by

$$q_{FP}(p) = \frac{\xi + (1-\xi)p}{(1+i)(1+\bar{b})} \tag{22}$$

which implies that the borrowing premium is $b_{FP}(p) = \bar{b}$ for all p under the definition in (21). As illustrated by the red line in Figure 4, while this alternative modeling is perfectly suitable to capture the existence of the large aggregate borrowing premium in the unsecured credit market, it ignores the varying effects of these premia across risk. Consequently, it fails to deliver the empirically accurately flatter profile of loan rate spreads.

4 Mapping the Model to the Data

This section describes our approach to calibrating our baseline model. We focus initially on the steady state for two reasons. First, our data indicate that variation in borrowing premia is much larger across borrowers than for specific borrowers across time, and focusing on steady state facilitates isolating the role of this cross-sectional variation. Second, the steady state of the model may be solved much more easily than the full stochastic equilibrium. Given our strategy for estimating the tightness of lending standards, this comes with significant computational advantages.[37] Sections 6.1 and 6.2 detail our calibration of the few additional parameters required for dynamic exercises.

Most parameters dealing with technology, the legal environment, and idiosyncratic shocks are set to standard values from the literature, described in the first subsection below. The remaining preference and lending standards parameters are then calibrated to match important credit market moments and the set of borrowing premia from Figure 2, described in the second subsection. The key innovation of our empirical approach comes from directly estimating the parameters of the $\lambda(\cdot)$ function to match empirical borrowing premia.

[37] Steady states solve in a few minutes, whereas full stochastic equilibria take several hours, making estimation costly. Appendices A.2.1, A.2.2, and A.2.3 present computational algorithms for deterministic steady state, perfect foresight transitions, and stochastic equilibrium, respectively. Section 6.2.1 discusses our approach to solving stochastic equilibria at a high level.

4.1 Parameters assigned outside the model

Panel A of Table 1 describes the key parameters which we specify outside the model. Risk aversion, capital share, and depreciation parameters are standard from the literature. The direct cost of default is set at 2% of median earnings as in Chatterjee et al. (2020). The probability of regaining access to the credit market, $\theta = 1/7$, is consistent with an average duration of limited credit access upon default of seven years. The recovery rate, $\xi = 16\%$, matches estimates from Call Report data between 1990 and 2020.[38]

The individual labor productivity process is taken from Storesletten et al. (2004). We choose this process since it captures the rich heterogeneity in earnings across individuals and allows for countercyclical earnings variance in the full business cycle model. The permanent and transitory components of this process are distributed log-normally around zero, with variances $\sigma_{\epsilon_1} = 0.448$ and $\sigma_{\epsilon_3} = 0.351$, respectively. The persistent component of the process follows an AR(1) process in logs, where the standard deviation of shocks is $\sigma_{\epsilon_2} = 0.129$ and the persistence is $\rho_{\epsilon_2} = 0.957$. The former number comes from averaging the estimates for recessions and expansions in Storesletten et al. (2004).[39] Figure A.1 in the Appendix shows that our earnings process closely matches the distribution of income observed in Y-14M.

4.2 Parameters estimated within the model

Strategy We estimate the nine preference and lending standards parameters in Panel B of Table 1 using the Simulated Method of Moments (SMM), targeting two sets of moments. We term the first set of six moments "credit moments." These include: (i) standard targets (default rate, fraction in debt, average spreads); (ii) the capital-output ratio; and (iii) two moments uniquely important to our model environment for reasons discussed below: average return on savings, and the share of total debt with low default risk ($1 - p < 10\%$). This latter moment is an especially critical target for our questions of interest given the shape of borrowing premia schedules observed in the data: our model must be consistent with the empirical fact that a large share of unsecured borrowing occurs at prices for which borrowing premia comprise the majority of the cost. The second set is comprised of eleven borrowing

[38] We compute recovery rates for each bank-quarter pair for the top 25 banks (98 percent of credit card assets in 2019) as the ratio of total recoveries to gross chargeoffs. We then weight across banks using the bank's share of credit card assets in the quarter, and then average across all quarters in the sample. Since recoveries may lag chargeoffs, we also compute the recovery rate in two additional ways for robustness. First, we use an annual basis rather than quarterly, comparing the sum of recoveries to the sum of chargeoffs for each year. Second, we use a 3 period right-aligned rolling quarterly sum for recoveries and a 3 period left-aligned rolling sum for charge offs. In all these exercises we find values ranging from 15.7% to 16.3%.

[39] The permanent and transitory components are discretized with 5 points. The persistent component is discretized into a 10-state Markov chain using the Tauchen method, which allows the grid points for ϵ_2 to remain the same as the transition matrix changes over the cycle by manipulating the "step size."

premia depicted in Figure 2. This leads to an over-identified system with seventeen target moments and nine parameters. We estimate the model by iteratively solving it for different sets of parameters, searching the parameter space using the Nelder-Mead simplex approach.[40]

To first order, the six preference parameters determine individuals' intertemporal and default behavior, pinning down the average levels of borrowing, saving, and rates of return in the first set of moments. As discussed in Section 3.9, the three lending standards parameters control the shape and level of the $\lambda(\cdot)$ function, which determines the size and covariance with repayment probability of borrowing premia. Of course, interactions and higher order effects imply that all of the parameters are jointly determined.

4.2.1 Estimated parameters

Discount factors Following Athreya et al. (2018) and Krusell and Smith (1998), we assume there are two β levels, with transitions governed by transition matrix Γ^{β}.[41] This process has four parameters: (i) the high β level, $\beta_H = 0.9835$; the difference between high and low β, $\beta_H - \beta_L = \Delta\beta = 0.3550$; (iii) the transition probability from β_H to β_L, $\Gamma^{\beta}_{HL'} = 0.0363$; and (iv) the transition probability from β_L to β_H, $\Gamma^{\beta}_{LH'} = 0.1223$. This process implies an average discount factor of $\overline{\beta} = 0.902$ ($\beta_L = 0.629$, with 77.1% high types). The gap between types is within the range of estimates from the literature and replicates a capital-output ratio of 3.0, a low bankruptcy rate, and a high share of low risk borrowing.

Other preference parameters We estimate that the non-pecuniary cost of default, or "stigma," is $\chi = 0.9010$, and the extreme value parameter is $\zeta = 0.1320$. The former helps pin down the bankruptcy rate and fraction of borrowers, controlling for the distribution of riskiness of borrowing. The latter implies that in the steady state of our model approximately 40% of default comes from agents for whom default is not the action delivering the highest "fundamental" value, consistent with the empirical fact that around 45% of default is driven by events other than income or job loss.

[40] Given the many non-linearities and complexity of solving our model, a derivative-based approach is infeasible. We have found that the Nelder-Mead method (attempted for many sets of initial conditions) yields consistent, stable results. Since this method searches over the entire real line, but some of our parameters are naturally bounded (e.g. $\beta \in [0, 1]$), we use transformations.

[41] Athreya et al. (2018) find that discount factor heterogeneity is crucial to capture the persistence of financial distress at the borrower level. Krusell and Smith (1998) (and others since) find that this also helps replicate the empirical distribution of wealth in the U.S. economy.

Parameter		Value	Target / Notes	Data	Model
Panel A: parameters assigned directly					
technology and legal					
average TFP	$\bar{z}$	1.000	normalization		
capital share	α	0.360	standard		
depreciation rate	δ	0.072	standard, annual model		
risk aversion	γ	2.000	CRRA preferences		
bankruptcy filing cost	κ	0.020	2% of median earnings		
prob. regain credit access	θ	0.143	7-yr avg. exclusion		
recovery rate	ξ	0.160	midpoint of estimates [0.157 - 0.163]		
labor productivity					
standard deviation, ϵ_1	σ_{ϵ_1}	0.448	permanent component, lognormal		
persistence, ϵ_2	ρ_{ϵ_2}	0.957	persistent component, AR(1) in logs		
standard deviation, ϵ_2	σ_{ϵ_2}	0.129	", std. dev. of innovations		
std. dev., ϵ_3 component	σ_{ϵ_3}	0.351	transitory component, lognormal		
Panel B: parameters estimated internally					
preferences					
extreme value scale	ζ	0.1320	bankruptcy rate (pp)	0.40	0.39
stigma	χ	0.9010	fraction in debt (pp)	11.7	11.8
high β level	β_H	0.9835	return on savings (pp)	5.00	4.89
difference, high and low β	$\Delta\beta$	0.3550	capital to output ratio	3.00	3.00
high to low β trans. prob.	$\Gamma^{\beta}_{HL'}$	0.0363	avg. loan rate spread (pp)	16.8	15.4
low to high β trans. prob.	$\Gamma^{\beta}_{LH'}$	0.1223	debt share with default probability $<$ 10% (pp)	74.7	76.9
lending standards			**See Figure 5**		
level	λ_0	165.0	SSE, credit moments	7.03	
location	λ_1	-0.0068	SSE, borrowing premia	2.76	
dispersion	λ_2	0.0826	combined SSE	9.79	

Table 1: **Baseline model parameterization and targeted moments**

Notes: The model period is annual. The labor productivity process is taken directly from Storesletten et al. (2004), Table 2 Row B. In Panel B, "credit moments" refer to those listed in the table; "borrowing premia" refer to the targets indicated in Figure 5. All moments are evenly weighted within category, and the combined SSE is computed as the sum of the two component SSE's.

Lending standards parameters Given the observed borrowing premium schedule in Figure 2, we assume that the lending standards function follows a (scaled) log-normal density:

$$\lambda(p) = \lambda_0 \exp\left\{-\frac{(\ln p - \lambda_1)^2}{2\lambda_2^2}\right\} \tag{23}$$

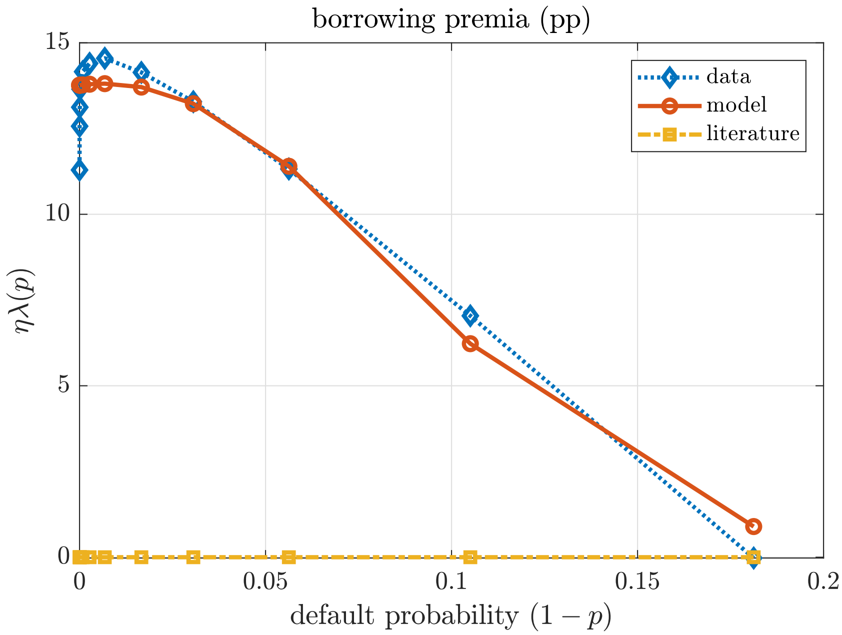

Figure 5: **Model fit to observed borrowing premia schedule**

We choose this functional form because it has four desirable properties. First, it bounds borrowing premia below by zero. Second, it generically has the shape we observe in Figure 2. Third, it provides these properties while limiting the number of parameters to estimate to three. Fourth, the curvature of the premium schedule is determined entirely by λ_1 and λ_2, so that only the level shifter parameter λ_0 interacts with the loan supply constraint.[42] This last property is especially relevant for our quantitative experiments in subsequent sections.

Under this specification, λ_0 determines the level of lending standards given the tightness implied the multiplier η. Importantly, this parameter is disciplined by our choice to match *both* the return on savings *and* the capital-output ratio, since η in our model is exactly the wedge between the return on savings ($\bar{i} = 1/\bar{q}$, where $\bar{q}$ is given by (19)) and the equilibrium interest rate (i, given by (18)). The interest rate i is determined by the capital-output ratio,[43] and so the gap i and $\bar{i}$ pins down $\eta = (1+\bar{i})/(1+i) - 1$. Thus by targeting both these moments we discipline the endogenous component of the schedule of borrowing premia, allowing us to identify the level parameter $\lambda_0 = 165$. The parameters $\lambda_1 = -0.0068$ and $\lambda_2 = 0.0826$ determine the curvature of the borrowing premia schedule. The former matches the peak close to zero of the hump-shaped distribution, while the latter matches the rate of decline in $1-p$.

[42] Alternative families of functions (logistic, beta density, etc.) do not fit the data as well. A more flexible (e.g. non-parametric) specification of $\lambda(\cdot)$ could likely match these premia even more closely, but at the cost of the tractability of our estimation procedure.

[43] Under Cobb-Douglas, the capital-output ratio is $K/Y = K/(K^\alpha N^{1-\alpha}) = (K/N)^{1-\alpha}$. The rental rate (6) may then be expressed as $r = \alpha/(K/Y)$, and the interest rate satisfies (18).

Model fit The right side of Panel B of Table 1 and Figure 5 provide an assessment of the model's fit to our set of targets. Turning first to borrowing premia, the model replicates the differences in borrowing premia across risk levels quite closely. One shortcoming is that we do not fully capture the large variation in observed premia for small changes in default probability in the immediate neighborhood of zero. We view this empirical variation as being driven by novel features of the credit card market at the very top of the credit score distribution not present in our model.

Our model matches almost exactly every targeted credit moment other than the average level of interest rate spreads, which is about 1.4 pp higher in the data than our model. This stems from the equilibrium interest rate in the model, which is a function of the capital-output ratio in our framework as discussed above. This implies a higher interest rate (about 4.8%) than many estimates of the real interest rate in recent years. Despite this slight discrepancy in the overall level of rates, though, matching the schedule of borrowing premia so closely still allows us to be consistent with the empirical distribution of the share of total debt by risk level (summarized, for example, by the share with default probability less than 10%). Moreover, our model replicates the distributions of wealth and labor income quite well, as Figure A.1 in the Appendix shows. While, unsurprisingly, our model does not capture the extreme concentration of wealth at the top of the distribution, it is in line with both the shape and concentration of the income distribution observed in the Y14-M data, a key component for our analysis.[44]

4.3 Model validation: credit outcomes across income levels

As discussed in Section 2.3 above, the variation in borrowing premia across income quartiles conditional on credit score (or, default probability) is much smaller than the analogous variation across credit scores conditional on income. This fact justified our simplified modeling approach whereby lending standards – and therefore borrowing premia – were determined at the default probability level only. Since default probability at the individual level is driven in large part by income in the model, though it is important to verify that our model delivers untargeted credit outcomes across income groups consistent with Y-14M data. Figure 6 presents results for two such moments.

Panels (a) and (b) of Figure 6 present debt to income ratios and the distribution of debt holdings across the model economy, respectively. They ask: given the empirically

[44]One caveat is that income information in the Y14-M data is at the account level. Thus, to the extent that income and number of credit cards are correlated, there could be a bias towards borrowers with more accounts. Using SCF data, though, Bird et al. (1999) find that among those holding credit cards, the number of cards is fairly flat across income groups. Further details on the construction of income are in the Appendix.

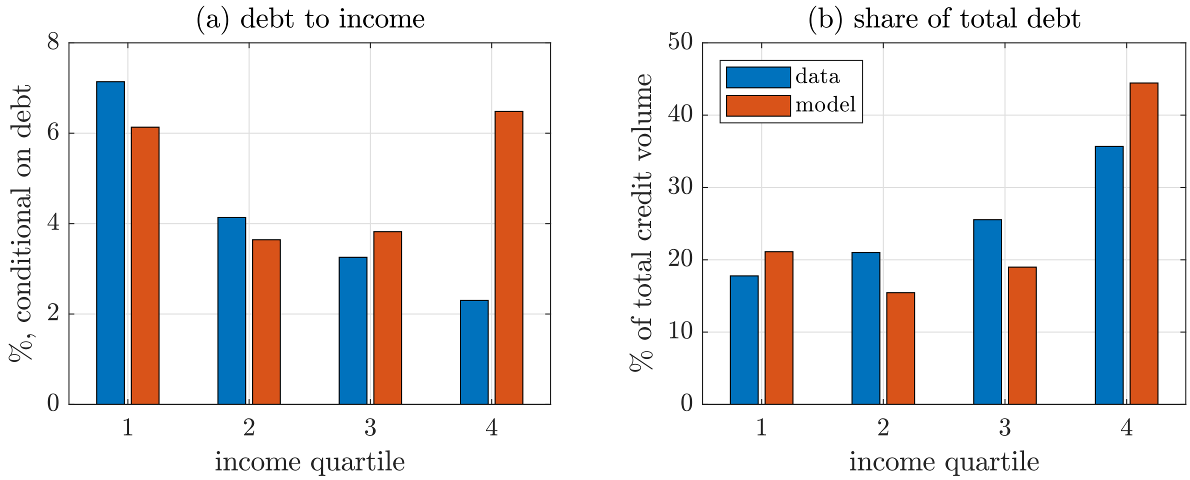

Figure 6: **Credit market moments by income quartile: model vs. data**

consistent credit *prices* agents face, do the choices they make deliver empirically consistent credit *outcomes* across the distribution of borrower incomes? This is a useful complement to our targeted moments, which ask the same question at the aggregated level. The answer, broadly, is yes. Panel (a) highlights that leverage at the borrower level tends to decrease with income for all but the very highest earners. Panel (b) verifies that these borrower-level leverage patterns appropriately aggregate since the model is consistent with the relative shares of total debt holdings across the income distribution. The most noticeable discrepancy here is that high earners in our model tend to take on more leverage than their empirical counterparts. Ultimately, though, this evidence supports the view that our model's pricing system generates empirically consistent borrowing behavior across the income distribution.

5 Quantitative Analysis I: Cross-Sectional Impacts

In this section we examine the steady state of the model in order to show how borrowing premia shape credit outcomes and welfare across the distribution of borrowers. By comparing our baseline model to three alternative economies, we quantify the effects of the level and incidence of lending standards on credit outcomes and welfare as well as the impact of their interaction with demand factors. The focus of this section is on cross-sectional implications; we leave our discussion of dynamics for Section 6.

5.1 Alternative economies

We consider our baseline and three alternative economies, whose main features are summarized in Table 2. These differences between the model economies fall into two categories: (i) how borrowing premia are determined in equilibrium ("determination") and (ii) how borrowing premia vary across borrowers and loans ("incidence"). The former refers to whether borrowing premia are determined endogenously within the model or specified as exogenous wedges. The latter refers to whether borrowing premia vary across the population of borrowers (as we observe) in the data.

Determination of borrowing premia The borrowing premium on a loan in our baseline model is the product of the endogenous multiplier on the aggregate loan supply constraint and the weight the loan receives in the constraint, as in equation (21): $b(p) = \eta\lambda(p)$. An alternative model which specifies $b(p)$ exogenously can also capture the schedule of borrowing premia we observe in the data.[45] Therefore, we compare our baseline model to this variant to highlight the role of the endogenous determination of borrowing premia.

With exogenously specified premia, constraint (17) is obviated and there is no multiplier η. This has two implications. First and most importantly, rather than estimating the lending standards function $\lambda(\cdot)$, we estimate the borrowing premium function $b(\cdot)$ directly. For consistency and ease of comparison, we assume the same specification for this $b(\cdot)$ function as we do for $\lambda(\cdot)$ in equation (23), simply replacing the parameters $\{\lambda_i\}_{i=0}^2$, with b_i. The resulting parameter values are presented in Panel B of Table 2. Our functional form for $\lambda(\cdot)$ (and $b(\cdot)$) ensures that we estimate $b_1 = \lambda_1$ and $b_2 = \lambda_2$ since these parameters fully specify the curvature of the schedule. The estimated level parameters b_0 and λ_0 differ, but $b_0 \approx \eta\lambda_0$ since both are disciplined by matching empirically observed borrowing premia (see the virtually identical SSEs). The slight difference comes from numerical tolerance. Second, there is no wedge between the equilibrium interest rate and the return on savings.

Incidence of borrowing premia Perhaps the most notable feature of the schedule of borrowing premia $b(p)$ in Figure 5 is its curvature with respect to default probability $1 - p$. In order to assess the role this curvature plays, we consider three alternative specifications. In all three, we use the model variant with exogenously specified premia in order to separate the role of determination from the role of how premia fall over the population. This also rules out having to compare across levels of the equilibrium multiplier η in the case of endogenous premia, which would not be invariant across these specifications.

The first alternative (column (2) in Table 2) shuts down our novel supply frictions completely by imposing that $b(p) = 0$ for all p ("no premia" economy). The second alternative (column (3)), includes a fixed exogenous borrowing premium which does not vary across borrowers or loans, making the level of borrowing premia orthogonal to borrowers' default

[45] The analogs of (19) and (20) for this economy are $\overline{q}(s) = \frac{1}{1+i(s)}$ and $q(\ell; x, s) = \frac{\xi+(1-\xi)p(\ell;x,s)}{(1+i(s))(1+b(p))}$.

Premia Determination	Endogenous	Exogenous		
Premia Incidence	Variable	None	Fixed	Variable
	(1)	(2)	(3)	(4)
Panel A: Differences in model properties				
shorthand	Baseline	Lit.	Lit.	-
constraint (17) applies?	Y	N	N	N
borrowing premia: $b(p) =$	$\eta\lambda(p)$	0	$\bar{b}$	$\tilde{b}(p)$
return on savings: $\bar{i} =$	$(1+i)(1+\eta)$	$1+i$	$1+i$	$1+i$
Panel B: Differences in calibrated borrowing premia				
level (b_0)	-	0	0.1108	0.1416
location (b_1)	-	0	1	-0.0068
dispersion (b_2)	-	0	∞	0.0826
SSE, borrowing premia	2.76	-	-	2.74

Table 2: **Names of and key differences between alternative economies**

Notes: Column (1) represents our "baseline" model. The dashes for the borrowing premia parameters represent the fact that b_0, b_1, and b_2 are not directly specified in the baseline model, but rather the lending standards parameters λ_0, λ_1, and λ_2 described in Table 1. Columns (2) through (4) all feature exogenously specified premia. In columns (2) and (3), "Lit." refers to "Literature," since both specifications appear in the literature. SSE refers to the sum of squared errors.

risk. Both of these alternatives have been used extensively in the unsecured credit literature. As described in Section 3.9, loan prices in this "fixed premium" economy are given by equation (22), which implies that $b(p) = \bar{b}$ for all p. We set $\bar{b} = 11.08\%$, the share-of-total-credit-weighted average borrowing premium in our sample. Therefore, the fixed premium economy is consistent with the average level of premia we observe, but not how they vary across borrowers. The third alternative (column (4)) allows borrowing premia to vary across borrower risk fully as observed in the data.

These three alternative economies allow us to highlight the impact of the higher level of interest rates implied by accounting for borrowing premia, as well as for the disparate effects of having these premia vary by risk. In addition, our analysis demonstrates the importance of determining premia endogenously, based on the tightness of the supply constraint with the implied general equilibrium effects.

5.2 How do lending standards impact the credit market?

Table 3 shows how key credit market moments and welfare change across steady states in our baseline economy and three alternatives. We consider our main findings on borrowing premia in three phases: (i) the impact of including them at all; (ii) the impact of their

Premia Determination	Endogenous	Exogenous		
Premia Incidence	Variable	None	Fixed	Variable
Moment (pp)	(1)	(2)	(3)	(4)
Panel A: Credit quantities				
fraction in debt	11.8	17.6	12.4	11.7
debt to income	5.02	9.14	4.25	4.94
total debt (not pp)	0.060	0.109	0.053	0.059
debt share, default prob. < 5%	64.2	86.2	86.8	64.1
debt share, default prob. < 10%	76.9	95.8	98.6	76.3
Panel B: Credit prices				
bankruptcy rate	0.39	0.30	0.18	0.40
average loan rate spread	15.4	1.74	12.9	15.8
interest rate, savings	4.89	4.94	4.88	4.88
interest rate, risk-free loan	19.2	4.94	16.0	19.2
Panel C: Consumption equivalent welfare				
mean	-0.29	-	-0.81	-0.70
standard deviation	1.44	-	1.99	1.49
skewness	-3.92	-	-4.92	-3.93
share in favor of switch (pp)	68.9	-	9.34	10.2

Table 3: **Credit market and welfare moments: baseline and alternatives**

Notes: All moments are expressed in percentage points (pp). Column (1) represents our "baseline" model economy, and the variants in columns (2) through (4) are summarized in Section 5.1. Welfare is computed in consumption equivalent terms. That is, defining the value of an agent in state x in the "no standards" economy to be $\overline{V}(x)$, and the value of the same agent in alternative economy $i \in$\{baseline, fixed premium\} to be $V_i(x)$, we compute $CE_i(x) = \left[\frac{V_i(x)+A(\beta(x))}{\overline{V}(x)+A(\beta(x))}\right]^{1/(1-\gamma)} - 1$, where $A(\beta) = \sum_{t=1}^{\infty} \prod_{i=0}^{t-1} \frac{\beta_i}{1-\gamma}$ is a term which adjusts for discount factor levels and transitions, as well as risk preferences γ. We aggregate using the equilibrium distribution of agents in the no premia economy.

incidence across risk levels; and (iii) the impact of determining them endogenously.

Including borrowing premia First, we assess the importance of including borrowing premia at all by comparing columns (1) and (2) of Table 3.[46] Total debt is 45% lower with borrowing premia. This reduction occurs along both the intensive and extensive margins (33% fewer borrowers). What drives these results? Introducing borrowing premia acts like tightening the borrowing constraint in a canonical incomplete markets model, promoting saving and discouraging borrowing as credit becomes more expensive for borrowers at all levels of risk. Borrowing premia imply a 14.3 pp wedge between savings and risk free loan

[46]Since the effect of endogenous determination is small in steady state as described below, one can also compare columns (4) and (2).

rates which cannot exist in the no premium economy. Similarly, the average loan spread in the baseline economy is 13.7 pp larger than in the no premia economy. Comparing the fixed premium economy (column (3)) to the no standards economy (column (2)), this intuition holds: all credit becomes more expensive, and households borrow less and save more.

Additionally, the composition of borrowers changes: the baseline economy has a 20 pp lower share of low risk borrowers than either the no premia or fixed premium economies. With a flatter price schedule (recall the illustration in Figure (4)), there is less disincentive to take on larger, riskier loans conditional on borrowing, which is consistent with the data. This effect, combined with the higher overall level of credit prices, yields 30% more default in the baseline economy than the no premia economy. However, as we argue next, it is not introducing premia that is key to this result, it is rather the incidence of the premia that is crucial in capturing the observed composition of borrowers' risk.

Incidence of borrowing premia Comparing columns (3) and (4) of Table 3 reveals how the incidence of borrowing premia drives the composition of debt by borrower risk. Since they imply a low elasticity of loan prices to default probability, the variable premia we document in the data induce borrowing at relatively high levels of risk, with more than 1/3 (1/4) of borrowing having default probability above 5% (10%). As a result, less borrowing occurs at low levels of risk in the variable case than the fixed case. Put differently, agents "pile up" where borrowing premia are low.

Moreover, since the fixed borrowing premium does not decline as risk premia increase, high risk loans are extraordinarily expensive in this economy. Thus borrowers choose small, low risk debts, reducing the debt to income ratio by 15% in the fixed premium economy relative to the baseline. Since the interest rate on a risk-less loan is lower under the fixed premium, however, the number of borrowers increases by 6%. These intensive and extensive margin effects combine to deliver 10% less total debt and over 50% less default in the fixed premium economy relative to the variable premia economy.

Determination of borrowing premia Comparing columns (1) and (4) shows that the two variable premia economies deliver quite similar credit outcomes. This is unsurprising since the borrowing premia schedules in the two cases are the same by construction. There is a slight (1 bp) difference in returns on savings from the effect of the endogenous multiplier. This small general equilibrium effect has modest welfare implications (discussed below). Ultimately, though, the endogeneity of borrowing premia maters much more for dynamic considerations (as shown in Section 6 below) than it does in steady state.

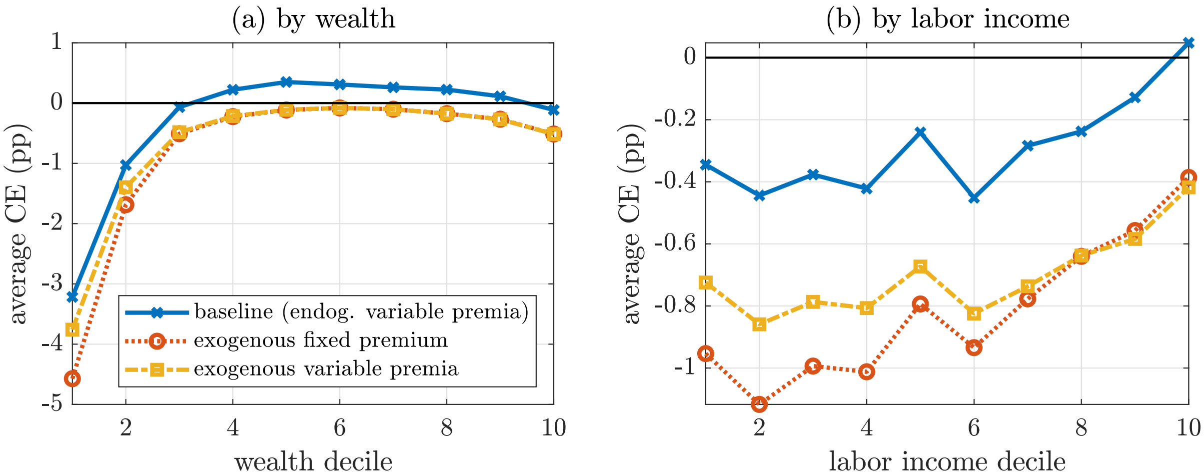

Figure 7: **Welfare distribution in alternative economies**

Notes: Welfare is computed in consumption equivalent terms. That is, defining the value of an agent in state x in the "no standards" economy to be $\overline{V}(x)$, and the value of the same agent in alternative economy $i \in$ {baseline, fixed premium} to be $V_i(x)$, we compute $CE_i(x) = \left[\frac{V_i(x)+A(\beta(x))}{\overline{V}(x)+A(\beta(x))}\right]^{1/(1-\gamma)} - 1$, where $A(\beta) = \sum_{t=1}^{\infty} \prod_{i=0}^{t-1} \frac{\beta_i}{1-\gamma}$ is a term which adjusts for discount factor levels and transitions, as well as risk preferences γ. We aggregate using the equilibrium distribution of agents in the no premia economy.

5.3 How do borrowing premia impact welfare?

Ultimately, though, what matters for borrowers is how borrowing premia affect the profile of consumption they can expect to attain during their lifetimes. For this reason, Panel C of Table 3 presents key moments of the distribution of welfare gains relative to the no premium economy. Figure 7 describes welfare metrics by income deciles relative to an economy with no standards for the baseline and fixed premium economies.[47]

Borrowing premia of any type are costly for borrowers. Accordingly, the average welfare gain is negative and economically significant for all economies with borrowing premia (-0.29%, -0.81%, and -0.70% for the baseline, fixed premium, and exogenous variable premia cases, respectively). Moreover, the distribution of welfare gains is extremely left-skewed in all cases since borrowing premia directly hurt current borrowers. While most agents prefer the no premia economy to the economies with exogenously-specified fixed or variable premia (90.7% and 89.8%, respectively), this reverses when premia are determined endogenously, with 68.9% of agents preferring the baseline economy to the no premia economy. What causes this reversal? While no one prefers less favorable terms of credit, savers receive a small benefit in the endogenous premia economy due to the small increase in the return on

[47]Welfare is computed in consumption equivalent units. We index welfare to the no premia economy since this is the most widely used frictionless benchmark. Additionally, Figure A.2 in the Appendix shows disaggregated consumption metrics (average consumption and its coefficient of variation) by income deciles in these economies.

savings. Though the average welfare gain remains negative, welfare losses are lower and most agents in fact prefer the endogenous premia economy to the no premia economy.

Figure 7 demonstrates that welfare losses are largest for agents with the least wealth and the lowest earnings. These agents are most likely to borrow in the near term, and therefore bear the brunt of the costs associated with borrowing premia. Moreover, Figure 7 highlights significant differences in the magnitude of welfare losses for these agents across model economies. Since poor, low-earning individuals tend to borrow at high risk, their credit is the most expensive and welfare losses the largest in the fixed premium economy. As wealth and income increase, the two exogenous premia cases converge in terms of welfare since the terms of credit for these agents become similar. Finally, the shape of the welfare distribution is essentially the same in both variable premia economies, but the GE effect discussed above shifts the level up with endogenous premia.

To this point, we have shown that borrowing premia impact borrowing and savings decisions sharply and have large implications for welfare. Fixing the average level of premia but changing their incidence reveals that these premia encourage borrowers to take larger, riskier loans. While the endogenous determination of borrowing premia has only a small effect on credit outcomes in steady state, it matters for our assessment of welfare gains.

6 Quantitative Analysis II: Dynamic Impacts

A key shortcoming of comparing steady states in the analysis above is that agents re-optimize and all market prices adjust to new long run levels when we change borrowing premia, and therefore the effective tightness of borrowing constraints. This is particularly relevant when comparing the exogenous variable premia and baseline economies, the latter of which accounts for the endogenous component of these premia but yields little difference in the ultimate allocation of credit. In reality, though, lending standards and borrowing premia change in response to economic conditions and the interactions between demand and supply factors, as indicated in our empirical analysis from Section 2. Therefore, in this section we analyze how shifts in lending standards and borrowing premia schedules alter responses to economic shocks. Crucially, our analysis allows us to distinguish the observed level of premia from the unobservable level of lending standards through the lens of the model.

We consider two exercises designed to underscore the dynamic impacts of shifts in lending standards and borrowing premia. First, we simulate a negative shock designed to reflect the current Covid-19 crisis. This allows us to: (i) measure the change in standards (the exogenous component of borrowing premia) separately from equilibrium effects on the demand for credit; and (ii) assess the impact of these changes in standards on credit and welfare. Central to this exercise is re-estimating the $\lambda(\cdot)$ function at the date of impact to match observed borrowing premia in the second quarter of 2020. Second, we analyze the full stochastic equilibrium of the model to understand how changes in lending standards over the business cycle drive the cyclical properties of the credit market.

6.1 How have lending standards shaped the response to Covid-19?

Given large recent disruptions in the unsecured consumer credit market during the Covid-19 pandemic, in this section we simulate a shock that matches key features of this downturn.[48] We address two key questions: (i) what do empirically observed shifts in borrowing premia tell us about shifts in standards in response to the shock?; and (ii) how did this estimated response of lending standards affect credit and welfare? Crucial to our approach to both questions is that we estimate the response of lending standards accounting for both the endogenous component (η), which summarizes the effect of increased demand for credit, and the exogenous component ($\lambda(\cdot)$), which mainly captures supply effects separate from this credit market tightness. Note that this approach is only possible in the version of our model in which borrowing premia are endogenously determined.

6.1.1 Calibrating the experiment and re-estimating $\lambda(\cdot)$

Our crisis shock has three exogenously specified components: TFP, earnings risk, and lending standards. The initial shock to TFP is 9.8% which generates a reduction in total output on impact of 9.8% as we observed in the second quarter of 2020. On impact, the variance of earnings goes from the steady state level $\sigma_{\epsilon_2} = 0.129$ to the recession level $\sigma^R_{\epsilon_2} = 0.163$, following Storesletten et al. (2004).[49] The persistence of the TFP and earnings shock, $\rho_z = \rho_\epsilon = 0.33$, is consistent with a three-year recession.

We estimate the shift in the lending standards function $\lambda(\cdot)$ to replicate the borrowing premium schedule observed in the March to June 2020 period in Figure 2.[50] This requires solving the impulse response for a set of candidate lending standards parameters and iterating on this procedure until the borrowing premia on impact match. Crucially, the shift in borrowing premia in the model comes from both endogenous tightening of the credit market

[48] Specifically, we simulate the shock together with a perfect foresight transition over the recovery.

[49] Table A.3 in the Appendix contains all the parameters relevant to this impulse response exercise. Figure A.5 in the Appendix illustrates the dynamics for these three shocks. While the specifics of this experiment are tailored to the Covid pandemic, the general dynamics are common to economic recessions. Note that with more current earnings data, we could potentially tailor the earnings component of the shock to the current crisis, but we choose this approach for transparency given current data limitations.

[50] For further information on changes in the interest rate schedule by borrower risk between the Covid period relative to the 2019 period, see Figure B.3b in the Appendix.

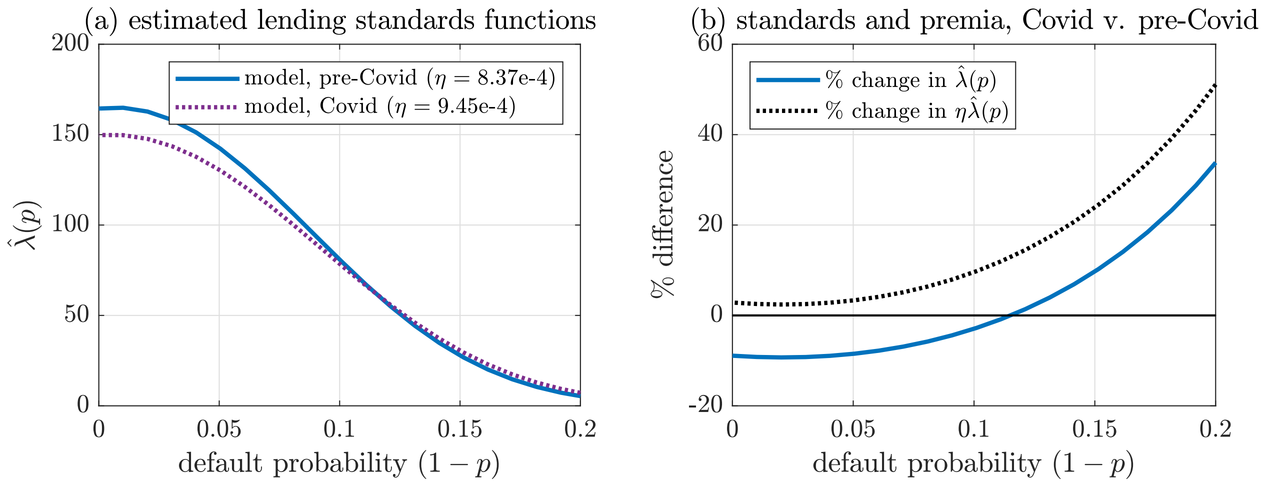

Figure 8: **Impact of estimated standards tightening**

Notes: This figure shows the implied interest rates and lending standards schedules for the parameters estimated in Tables 1 and A.3 for pre-Covid and Covid periods, respectively. Percentage differences are computed with 2019 ("pre-Covid")as the base year.

(higher η) and changes in $\lambda(\cdot)$, which proxies banks' responses on top of this effect. Given early signs that the initial credit market tightness is being undone quickly, we assume a lower persistence of the lending standards process, $\rho_\lambda = 0.25$. The fit of our model's borrowing premium schedule to its empirical counterpart is shown in Figure A.4 in the Appendix; as in our baseline, the model fits the data closely.

6.1.2 What does our estimation imply about lending standards?

One insight underpins our methodological approach: given a structural specification of lending standards via constraint (17), we can use our estimates of the parameterized function (23) from Tables 1 and A.3 to infer lending standards as proxied by the $\lambda(\cdot)$ function. The results of this analysis are presented in Figure 8. We first discuss our findings on standards within the model, then consider how they compare to survey evidence on lending standards.

Estimated shift in lending standards Compared to our baseline, on impact we estimate a lower level of standards, with λ_0 declining by 4.24%. This is accompanied by a significant (31.1%) rightward shift in the location parameter λ_1, and a 7.18% increase in the variation parameter λ_2. As the blue line in panel (b) of Figure 8 shows, these parameter shifts imply that the level of standards eased, but that standards "rotated against" higher risk borrowers, resulting in a net tightening for them. The shift in the schedule of borrowing premia (black line, panel (b)) inherits the estimated shape of the shift in lending standards, but premia rise across all levels of risk due to the equilibrium response of the loan constraint multiplier

η, which rises by 12.9% on impact.

Validation: how do standards in our model compare to survey evidence? Since this lending standards mechanism is the key novelty of our work, we compare our results to survey evidence from the Senior Loan Officer Opinion Survey (SLOOS) before discussing how the response of standards shapes credit and welfare outcomes. It is difficult to incorporate survey data on lending standards directly into a quantitative model because survey responses are qualitative, and the quantitative diffusion indices which summarize them have no direct analog in the model. Still, this qualitative evidence can provide useful validation of our quantitative findings.

Figure 9 plots measures of the tightening or easing of standards using a diffusion index assembled from SLOOS responses.[51] The key insight is that lending standards for credit card loans are tighter in recessions than expansions. They start tightening in the lead-up to downturns and subsequently ease gradually after recessions. This is also true for the relevant credit terms – interest rate spreads and credit limits –, and our model captures these observed patterns (see Figure B.4 in the Appendix).

These diffusion indices do not allow any clear way to directly disentangle aggregate or equilibrium effects from bank-specific supply choices, but banks' responses to special questions regarding the levels of lending standards and the reasons for tightening standards provide validation for our results. As shown in Figure B.5b in the Appendix, in the October 2019 SLOOS, banks cited as main reasons for reduced willingness to approve credit card applications: (i) concerns related to borrowers' ability to consistently make payments; (ii) expected deterioration in portfolio quality; (iii) a less favorable or more uncertain economic outlook; and (iv) a reduced tolerance for risk. This suggests the importance of the market-wide shift credit demand factors captured by our endogenous multiplier.

What about borrower-specific factors? In our model, *premia* tighten for all borrowers in response to the shock, but *standards* tighten only for high risk borrowers and loans. This suggests that, in a sense, credit supply has shifted to the low risk segment of the market from the high risk, pointing to improved terms of credit for low risk borrowers. We find evidence for this differential shift in the October 2019 SLOOS.[52] As shown in Figure B.5a in the Appendix, banks reported they were less likely to approve such loans for borrowers with FICO scores of 620 in comparison with the beginning of the year, while they were about as

[51] The construction of this index and the SLOOS data in general are detailed in Appendix B.2.1. Broadly, this index takes the responses of banks on tightening or easing lending standards and weights them by banks' shares of total credit card lending. The patterns we document hold broadly for all categories of bank loans.

[52] This vintage of the survey included a set of special questions asking banks to assess the likelihood of approving credit card applications by borrower FICO score in comparison with the beginning of the year.

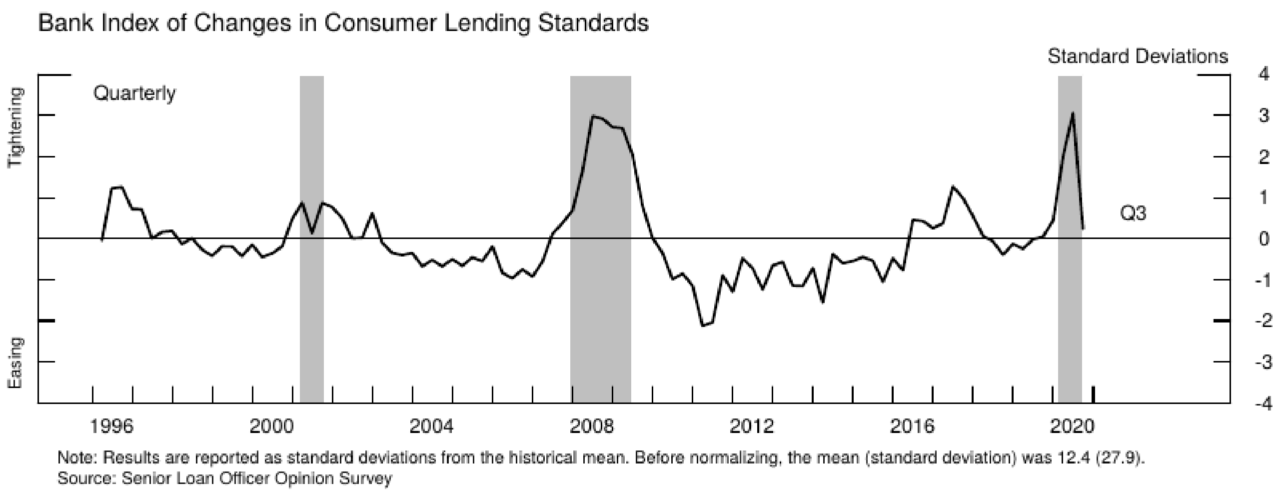

Figure 9: **Lending standards for credit card loans**

likely to approve such loans for borrowers with FICO scores of 720 over this same period. This implies that banks do not change standards uniformly across borrowers. In particular, when tightening standards, banks typically tighten more for low credit score borrowers.

6.1.3 The role of response in lending standards

There has been extensive policy discussion about the role of banks' willingness to provide credit in the current downturn, focusing on the impact of changes in bank lending policies on credit supply across the population. There has been particular concern for riskier borrowers who may have the most exposure to the economic downturn associated with the Covid crisis. This section addresses these concerns directly by highlighting the role the estimated response of lending standards played in shaping the response to the crisis. Since this analysis hinges on isolating the effects of specific components of the response of standards through counterfactuals, we first describe the cases we consider.

Types of responses We simulate the Covid shock for five separate cases of the model, as described in Table 4. First, we consider the baseline case estimated above (column (3)). Second, we consider the "no premia" version of the model (column (1)). Third, we consider the case where borrowing premia are determined and estimated exogenously, but yield the same response as in the baseline ("exogenous full," column (2)). Lastly, we consider two alternatives responses of the lending standards function $\lambda(\cdot)$ in the baseline specification: (i)

Determination		N/A	Exogenous	Endogenous		
Incidence		None	Variable			
Response		N/A	Full	Full	None	Level Only
		(1)	(2)	(3)	(4)	(5)
Panel A: Different responses across cases						
model object shifted		-	$b(p)$ directly	$\lambda(p)$	$\lambda(p)$	$\lambda(p)$
level shift?		-	Y	Y	N	Y
rotation?		-	Y	Y	N	N
Panel B: calibration of responses across cases						
initial						
level	λ_0, b_0	-	0.1416	165.0	165.0	165.0
location	λ_1, b_1	-	-0.0068	-0.0068	-0.0068	-0.0068
dispersion	λ_2, b_2	-	0.0826	0.0826	0.0826	0.0826
impact						
level	λ_0', b_0'	-	0.1480	158.0	165.0	158.0
location	λ_1', b_1'	-	-0.0047	-0.0047	-0.0068	-0.0068
dispersion	λ_2', b_2'	-	0.0885	0.0885	0.0826	0.0826
SSE, premia on impact		-	1.32	1.40	-	-

Table 4: **Different responses of standards and premia across alternative economies**

a case in which $\lambda(\cdot)$ does not shift in response to the shock, ("endogenous none," column (4)); and (ii) a partial response to the shock, in which the level λ_0 shifts down as estimated but there is no rotation, i.e. λ_1 and λ_2 are kept at their steady state levels ("level only," column (5)). In all cases in columns (3) through (5), the endogenous component of borrowing premia, η, is free to adjust as demand for credit increases in response to the shock. For all cases with borrowing premia, we assume the variable incidence we document in the data.

These scenarios isolate the contributions of different facets of the response of standards to the shock. First, they highlight the effect of accounting for borrowing premia at all (no premia (1) vs. baseline (3)). Second, they demonstrate how the endogenous determination of borrowing premia affects the response to the shock (exogenous (2) vs. baseline (3)). Third, they show the role of the "level" and "rotation" effects standards estimated above (comparing columns (3), (4), and (5)). These cases also underscore the relative importance of bank-driven supply factors, modeled as exogenous shifts in standards.

Credit market outcomes Table 5 summarizes how the key credit market variables respond to the shock in these five cases using a "peak-to-trough" analysis.[53] First, the large

[53]Figure A.5 in the Appendix shows the full paths for key variables across all cases considered.

Determination	N/A	Exogenous	Endogenous		
Incidence	None	Variable			
Response	N/A	Full	Full	None	Level Only
max % diff, pre- to post-shock	(1)	(2)	(3)	(4)	(5)
Panel A: Credit market variables					
total debt	6.85	8.74	6.61	6.43	6.83
debt to income	11.2	12.7	11.0	11.0	11.0
fraction in debt	5.98	8.25	6.17	5.43	6.92
bankruptcy rate	25.1	31.9	45.1	43.3	41.0
average loan rate spread	22.9	9.40	15.0	17.2	13.0
return on savings	-1.12	-1.17	-1.02	-1.02	-1.03
loan constraint multiplier	-	-	20.6	20.8	20.2
Panel B: Consumption equivalent welfare					
mean	-	-0.70	-0.35	-0.35	-0.34
standard deviation	-	1.55	1.56	1.55	1.53
skewness	-	-4.24	-4.18	-4.14	-4.16
share in favor of switch (pp)	-	9.69	68.1	68.1	68.1

Table 5: **Covid shock: peak responses across model variants**

Notes: This table presents the maximum percentage difference from the pre-shock steady state along the impulse response path back to steady state for the indicated model variant. Differences in specification along determination, incidence, and response are summarized in Table 4.

differences between the baseline and no premia economies (columns (3) and (1)) reveal the importance of accounting for borrowing premia. Price responses vary sharply, with the average loan spread spiking 52.6% higher in the no premia economy. The large effect in the no premia economy arises because loan prices depend solely on risk premia, and so the increase in default risk feeds fully into prices. By contrast, although the baseline economy features an even larger shift in default risk, the price effect is smaller because the shape of borrowing premia implies flatter price schedules.

These differential pricing changes only tell part of the story, though, and we must still consider the very different levels of prices and credit volumes across these economies (refer back to Table 3). For example, even though the response of interest rates is larger in the no premia economy, the bankruptcy rate rises by 20 pp more in baseline economy. Intuitively, unsecured credit is still relatively cheap in the no premia economy, even with the shift in spreads. As such, the absence of borrowing premia makes credit more attractive and exclusion from the market more costly, limiting the uptick in bankruptcy. Relatedly, even with the higher steady state level of credit in the no premia economy (in total and on both the intensive and extensive margins), total credit increases on impact by 3.6% more with no premia, driven by an intensive margin, or leverage, effect.

Second, comparing the two economies in which borrowing premia respond exactly as in the data (determined exogenously in column (2) and endogenously in (3)) highlights the novel effects of our credit supply mechanism. Endogenous determination matters, with the average spread and bankruptcies rising 37.3% and 29.2% less, respectively, when premia are determined exogenously. In addition, total debt increases much more along both the intensive (15.5%) and extensive (33.7%) margins with exogenously determined premia.

With loan prices adjusting in exactly the same way across these simulations by construction, what drives these effects? In our baseline economy, the multiplier η increases as the credit market tightens; by contrast, this effect is absent with exogenous premia. This multiplier affects the pricing of both loan *and* savings contracts, and in particular it dampens the effect of the drop in the real interest rate: the return on savings declines by 14.7% more on impact in the exogenous premia case than in the baseline. This induces agents to save more and demand less credit on the margin, especially higher wealth or income individuals who rely less on unsecured credit saving. This effect "selects" a relatively riskier pool of borrowers in the baseline economy.

Third, comparing columns (3) and (5) disentangles the roles of the upward level shift and outward rotation in the response of standards. In the case with only a level shift (column (5)), total credit volume increases by 3.3% more than in the baseline economy, driven almost entirely by the extensive margin. Spreads and bankruptcies also increase by less in this case. These results arise because the pure level shift actually represents an *easing* of standards, evidenced by the smaller (by 40 bp) rise in the multiplier. Since this economy suppresses the nonuniform adjustment of standards, where high risk borrowers face worse relative terms of credit, these agents find borrowing relatively more attractive on impact in economy (5).

Lastly, comparing columns (3) and (4) illustrates the effect of the full standards response, since economy (4) holds the $\lambda(\cdot)$ function at its pre-crisis specification. Since this specification lacks the downward level shift in λ_0, it induces a 2.2 pp larger increase in average spreads than the baseline. Since the credit market becomes tighter, the multiplier η increases by 20 bp more than in the baseline. The increase in credit decreases by 12.0% on the extensive margin, and peak bankruptcies fall slightly as well. Ultimately, the economy in which standards do not respond at all demonstrates the critical importance of the downward level shift in standards, even as they tighten against higher risk borrowers.[54]

[54]To keep focus on the effect of the tightening of standards, our analysis abstracts from accounting for banks' policies in allowing forbearance and related payment relief programs to their clients, as it has been the case in response to the Covid crisis. Data show that forbearance rates for consumer loans have been about ten percent over the second quarter in 2020 and so the effect on default that we find should be interpreted with caution and considered as an upper bound. Nevertheless, our comparative analysis is robust to this omission

Welfare How do the different components of the response of lending standards to the shock affect agents' welfare? To address this question, we analyze the welfare gains and losses across these five cases relative to the economy with no premia.[55] We report key moments of the welfare distribution in panel B of Table 5.

Unsurprisingly, Table 5 reflects our steady state finding that premia are costly: welfare gains relative to the no premia economy are negative on average and sharply left-skewed in all four cases with borrowing premia. Our dynamic analysis presents two additional novel results, though. First, the increased return on savings with endogenously determined premia mitigates welfare losses by about half on average (-0.35% vs -0.70%). In fact, more agents narrowly benefit from this general equilibrium effect than are hurt by borrowing premia, and so 68.1% of the population prefers any of the endogenous economies, compared to only 9.7% in the exogenous case.[56] Second, the specific nature of the response of lending standards has only small effects in terms of welfare. This stems from the fact that most agents can move along the borrowing premia schedule by adjusting their choice of loan, an effect which would be muted if loan terms depended more exclusively on borrower traits than borrower choices. The case with the "loosest" standards is the level only response in column (5), and this case has the smallest welfare loss. Figure A.6 in the Appendix illustrates the distribution of welfare losses across wealth and income in each economy. In all cases, as in steady state, agents actually borrowing (low or negative wealth) are the most impacted by premia. We next turn to studying the role of lending standards across the business cycle.

6.2 How do lending standards affect the business cycle?

Given the results from Section 6.1, it is natural to wonder how these dynamics play out in an environment with regularly occurring aggregate shocks. To this end, we now present results from the full stochastic equilibrium model in order to highlight the role lending standards play in shaping credit market and consumption outcomes over the business cycle. We first describe the additional parameters we calibrate for the full model and our solution method, then present our main results.

as our assumptions regarding these additional programs are kept the same across all three economies.

[55] We measure welfare losses using the recursive definition of the value function to compute consumption equivalent welfare along the transition path.

[56] Although there is no GE effect through the multiplier η with exogenous premia, there is still a GE effect insofar as aggregate capital shifts differentially in response to the shock depending on the specification of borrowing premia. This effect is small compared to the multiplier effect, though.

6.2.1 Calibration and computation

As in simulations above, we must calibrate processes for TFP, earnings, and lending standards. We posit that TFP follows an AR(1) process discretized into two points. We assume the recession and expansion levels are symmetric around the steady state level $\overline{z}$, moving up and down by a factor of $\Delta_z = 0.0198$, chosen to match the standard deviation of output (1.20%). We set the share of low TFP periods, $s_R = 0.211$, to match the average frequency of recessions (about 1 every 5 years). Finally, we choose the probability of exiting a recession, $\Gamma_{RE'} = 0.667$ to be consistent with an average recession duration of 1.5 years.

We again follow Storesletten et al. (2004) for the earnings process, setting the standard deviation of the persistent component almost twice as high in recessions ($\sigma^R_{\epsilon_2} = 0.163$) as in expansions ($\sigma^E_{\epsilon_2} = 0.094$). The persistence is held constant at $\rho_{\epsilon_2} = 0.957$ across aggregate states. Finally, we assume that lending standards in expansions follow our baseline specification (FY2019), while those in recessions follow the parameterization estimated in the impulse response exercise. Given that we only have reliable Y-14M data dating back to 2014, we are unable to measure borrowing premia in historical recessions outside the current one, which limits our ability to perform a richer estimation of the $\lambda(\cdot)$ function over the cycle. Table A.1 summarizes the calibration used in this section.

The key challenge we face in solving for stochastic equilibria is that endogenous aggregate state variable μ, the distribution over idiosyncratic states, is potentially infinite-dimensional. To overcome this challenge, we follow the Krusell and Smith (1998) state space approximation procedure, whereby households summarize the distribution with a finite number of moments which determine aggregate prices, and forecast these moments based on current observables. Our solution procedure adapts this approach with two important modifications. First, the households must be able to forecast the equilibrium value of the multiplier on the loan constraint, η, in order to evaluate choices given the pricing equations (19) and (20). Thus, households in our model use an additional forecasting rule, beyond those required for aggregate capital and labor productivity. Second, during the simulation step of the Krusell-Smith algorithm, we must bisect and recompute decision rules at each period in order to solve for the exact equilibrium η in each period. This increases the computational burden associated with solving the model substantially. Appendix A.2.3 describes the algorithm in detail, and Table A.2 presents the converged forecasting rules across model specifications.

6.2.2 Business cycle results

Table 6 presents key cyclical properties from our business cycle analysis for the baseline and no premia versions of our model economy, along with their data counterparts. Beginning

Determination	Data		N/A		Endogenous	
Incidence	-		None		Variable	
Response	-		N/A		Full	
Moment	σ_X/σ_Y	ρ_{XY}	σ_X/σ_Y	ρ_{XY}	σ_X/σ_Y	ρ_{XY}
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Macro aggregates						
output	(1.20%)	(1.00)	(1.20%)	(1.00)	(1.20%)	(1.00)
consumption	0.81	0.92	0.15	0.87	0.21	0.97
Panel B: Credit quantities						
total credit card debt	3.20	-0.29	0.72	-0.86	0.59	-0.90
bankruptcy filings	17.9	-0.11	4.31	-0.96	10.0	-0.76
debt to income	5.23	-0.27	1.11	-0.99	1.76	-1.00
fraction in debt	6.62	0.48	0.49	-0.83	0.25	0.24
Panel C: Interest rates						
IR, savings	0.15	0.23	0.27	0.55	0.29	0.42
IR, risk free loan	0.19	-0.56	0.27	0.55	2.45	-0.74
IR, all loans	0.90	-0.88	0.92	-0.95	2.53	-0.81

Table 6: **Business cycles: data, baseline, and no premia economies**

Notes: Business cycle moments are computed using HP filtered logs of the data, with annual smoothing parameter of 6.25. Standard deviations are normalized by the standard deviation of GDP, and correlations are with GDP. Data are for 1999-2019 except for risk free loan rate and debt to income for which we use Y-14M data. Details of data sources are provided in the Appendix. For the measure of default used in Section 2, the relative volatility and cyclicality are 5.11 and -0.29.

with Panel A, our baseline model delivers 60% more consumption volatility than the no premia model, despite the same fundamental volatility of output. It is well-known in the literature that one-asset or "net wealth" models such as ours tend to under-predict consumption volatility. While this is still true in our case, the baseline economy improves quite a bit on this margin. Turning to credit quantities in Panel B, our analysis delivers two key findings: (i) bankruptcy filings are more than twice as volatile and less countercyclical in our baseline economy than the no premia economy, bringing these moments more in line with the data; and (ii) the extensive margin of credit usage is procyclical in our baseline as in the data, unlike in the no premia economy.

Panel C highlights that these key results flow from the dynamic pricing mechanism revealed by our transition experiments. Specifically, in both economies, the interest rate on savings is procyclical while average interest rate spreads on loans are countercyclical. In our baseline, though, this countercyclicality applies to loans of *all risk levels*, even including risk-free loans. By contrast, low risk loans become cheaper in relative terms in an economy with no premia, driven by the drop in the benchmark interest rate. As in Nakajima and Rios-Rull (2019), the countercyclicality of income risk induces risk premia to rise unconditionally, and agents counteract this unconditional effect by shifting into less risky loans. In our model, however, across-the-board increases in borrowing premia make credit more expensive even controlling for borrowers' responses. This effect is novel to our framework, coming from the lender side of the model. With procyclical credit usage and countercyclical rates for all risk loans, consumers' ability to use unsecured credit to insure against risk across the business cycle is diminished, reflected in increased consumption volatility. Put together, this set of results strengthens our view that an economy with endogenous premia significantly improves on consumer credit theories with aggregate risk.

7 Conclusion

We provide evidence for large borrowing premia above risk premia in the U.S. credit card market which are absent from standard unsecured credit models. To close this gap between data and theory, we propose a model that incorporates tractably specified supply frictions – a flexible form of "lending standards" – into a model of unsecured credit. We estimate this model to match the empirical incidence of borrowing premia. By analyzing in detail the effects of the variable incidence, endogenous determination, and estimated response of borrowing premia, we argue that our model performs better than alternative specifications: accounting for these premia matters when studying how unsecured credit shapes economic outcomes and welfare. Our paper makes four important contributions.

First, we document the existence of large, non-uniform borrowing premia in the unsecured credit market. By combining data from Y-14M and Equifax, we document a relatively flat relationship between interest rate spreads and default probability, highlighting the existence of borrowing premia that decline with borrower risk. This finding holds both when controlling for borrowers' income and across "normal" and "crisis" periods. Borrowing premia rise across the board in crises, but rise the most for high risk loans. These dynamics are consistent with survey evidence on lending standards and terms of credit from the SLOOS.

Second, we augment standard unsecured credit models by including supply frictions which deliver endogenous loan prices consistent with these observations. Our novel modeling and estimation approach is flexible: an appropriate choice of "lending standards," modeled as risk weights in a constraint on aggregate loan supply, can jointly match any observed schedule of borrowing and risk premia. Crucially, borrowing premia in our model include both an endogenous component tied to credit market tightness and an exogenous component which accounts for heterogeneity in premia.

Third, we demonstrate the importance of accounting for borrowing premia in the cross-section. Both the overall level of borrowing premia and their incidence across risk levels matters. The former effect raises the overall price of credit, disincentivizing borrowing on both intensive and extensive margins. The latter effect induces borrowers to substitute into larger, higher risk loans in equilibrium since the largest borrowing premia are associated with small, low risk loans. Borrowing premia are extremely costly in welfare terms, especially for low wealth and low income individuals.

Fourth, we show that borrowing premia and their dynamics shape credit market dynamics over the business cycle. In response to a negative shock, borrowing premia tighten across the board, but do so more for relatively high risk borrowers. We find that while the level effect is driven by endogenous credit market tightening, the incidence effect is driven by the "rotation" of lending standards. This tightening of borrowing constraints limits households' ability to use debt to smooth consumption in response to a shock resulting in significant welfare losses. Over the business cycle, these forces play out in a similar way, and shifts in borrowing premia drive the cyclical properties of the unsecured credit market.

Our analysis presents three main limitations, which we view as avenues worth pursuing in future research. First, we interpret additional costs of borrowing in excess of those implied by measurable default risk as arising from supply frictions which we model exogenously. While sufficient for the measurement purposes in this paper, this approach is silent on the origin of these costs. Future research accounting for regulatory constraints or search frictions, for example, would provide further insights on the mechanics behind setting loan policies.[57] Second, our empirical findings reveal the importance of non-price terms of credit in the unsecured credit market. For example, we find large variation in credit card limits across borrower risk, which implies a nonuniform relationship between credit limits and probability of default akin to what we emphasize for spreads.[58] While our model delivers some measures of credit limits and pushes the paradigm prevalent in the literature much further, it does not fully account for the level and incidence of these important non-price terms of credit. Third, the limited time span of Y-14M hinders our ability to consider recession episodes before the 2020 recession. Related, the particularities of the Covid crisis – government support via stimulus checks, expanded unemployment benefits, specific income shocks, etc. – are likely to change households' borrowing and saving behavior. We hope to tackle these facets of our analysis as more data become available.

[57]In Castro et al. (2020), a companion paper in progress, we empirically analyze these mechanics and drivers of changes in standards across banks using matched survey data on banks' lending policies with detailed data on banks' loan portfolios.

[58]See Figure B.2 in the Appendix. Furthermore, banks' SLOOS responses suggest that non-price terms are a large margin of adjustment over the cycle.

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Appendix for "Lending Standards and Borrowing Premia in Unsecured Credit Markets"

A Model and Quantitative Appendix

A.1 Derivation of pricing conditions

The first order conditions of maximizing the bank objective (16) subject to (17) are

$$\begin{aligned} 1 &= \frac{1}{1+i(s)}\mathbb{E}_{s'|s}\left[W_K(K',\mathcal{M}';s')\right] \\ q(\ell;x,s)\ell\left(1+\eta\mathbf{1}[\ell>0]+\eta\lambda(p(\ell;x,s);z)\mathbf{1}[\ell<0]\right) &= \frac{1}{1+i(s)}\mathbb{E}_{s'|s}\left[W_{m(\ell;x,s)}(K',\mathcal{M}';s')\right] \end{aligned}$$

and the corresponding envelope conditions are

$$\begin{aligned} W_K(K,\mathcal{M};s) &= 1+r(s)-\delta \\ W_{m(\ell;x_{-1},s_{-1})}(K,\mathcal{M};s) &= -\int_{\mathcal{X}}\left(1-g_d(\ell;x,s)+\xi g_d(\ell;x,s)\right)\ell\Pr(x_{-1},dx). \end{aligned}$$

Combining these expressions, and applying the definition of expected repayment probability from equation (15), delivers equations (18), (19), and (20) from the main text.

A.2 Computational algorithms

We describe the key computational algorithms used in this model in three phases. First, we describe how to solve for the steady state of the model. Since this is the simplest case in our framework, we use this case to be extremely explicit. Then, in the next two phases, we describe the key departures needed to compute transitions (or, equivalently, impulse responses) and the full business cycle version of the model.

A.2.1 Steady state

In the steady state of the model, the variance of the aggregate shock is set to 0. As a result TFP is constant through time, and the equilibrium is stationary. We can therefore solve the model using a standard algorithm in the vein of Chatterjee et al. (2007).

1. Make an initial guess of the equilibrium aggregate capital stock, K_0. Since labor supply is exogenous, total effective labor units N are fixed, and we can compute the implied rental, wage, and real interest rates via (6), (5), and (18), respectively.

2. Make an initial guess of the equilibrium multiplier on the loan supply constraint (17), η_0. This implies an equilibrium savings price according to equation (19).

3. Make an initial guess of the expected repayment probability function across all states, p_0. This implies an equilibrium loan price schedule according to equation (20).

4. Use value function iteration to solve the household problem (7) – (12).

5. Use the default decision rule from step 4 and equation (15) to compute the implied repayment probability function, p_1. If $\sup|p_1 - p_0|$ is within tolerance, proceed to step 6. Otherwise, set $p_0 = \psi_p p_1 + (1-\psi_p)p_0$ (where $\psi_p \in (0,1]$ is a relaxation parameter) and return to step 3.

6. Solve for the stationary distribution $\mu(x)$.

   (a) make an initial guess of the distribution $\mu_0(x)$.

   (b) update $\mu_1(x) = T^*\mu(x)$, where the operator T^* is defined as follows:

$$
\begin{aligned}
T^*\mu(a', \beta'\epsilon', 0) &= \underbrace{\int \Gamma^{\beta}(\beta,\beta')\Gamma^{\epsilon}(\epsilon,\epsilon')(1-g_d(x;s))\mathbf{1}\left[a' = g_a(x;s))\right] d\mu_0(a,\beta,\epsilon,0)}_{f=0,d=0} \\
&\quad + \underbrace{\theta \int \Gamma^{\beta}(\beta,\beta')\Gamma^{\epsilon}(\epsilon,\epsilon')\mathbf{1}\left[a' = g_a(x;s))\right] d\mu_0(a,\beta,\epsilon,1)}_{f=1,\text{ lose flag}} \qquad \text{(A.1)} \\
T^*\mu(a', \beta', \epsilon', 1) &= \underbrace{\int \Gamma^{\beta}(\beta,\beta')\Gamma^{\epsilon}(\epsilon,\epsilon')g_d(x;s)\mathbf{1}\left[a' = g_a(x;s))\right] d\mu_0(a,\beta,\epsilon,0)}_{f=0,d=1} \\
&\quad + \underbrace{(1-\theta) \int \Gamma^{\beta}(\beta,\beta')\Gamma^{\epsilon}(\epsilon,\epsilon')\mathbf{1}\left[a' = g_a(x;s))\right] d\mu_0(a,\beta,\epsilon,1)}_{f=1,\text{ keep flag}} \qquad \text{(A.2)}
\end{aligned}
$$

   (c) if $\sup|\mu_1 - \mu_0|$ is within tolerance, proceed to step 7. Otherwise, set $\mu_0 = \mu_1$ and return to step 6b.

7. Compute the left and right hand sides of the constraint (17):

$$
\begin{aligned}
\chi^-(\eta_0) &\equiv -\sum_x \lambda(p(g_a(x);x))q(g_a(x);x)g_a(x)\mathbf{1}[g_a(x) < 0]d\mu(x) \\
\chi^+(\eta_0) &\equiv \sum_x \bar{q} g_a(x)\mathbf{1}[g_a(x) > 0]d\mu(x)
\end{aligned}
$$

   (a) if $\chi^+ > \chi^-$ and $\eta = 0$, proceed to step 8. Otherwise, go to step 7b.

   (b) use bisection to compute an updated guess of the multiplier implied by current aggregate loan demand and savings supply, η_1. Specifically, assume that the repayment probability function, decision rules, and stationary distribution remain unchanged, but update η – and therefore the savings and loan prices (19) and (20) – until $|\chi^+ - \chi^-|$ is within tolerance.

   (c) set $\eta_0 = \psi_\eta \eta_1 + (1-\psi_\eta)\eta_0$, and return to step 2.

8. Compute the aggregate capital implied by the equilibrium stationary distribution, $K_1 = \sum_x a(x)\mu(x)$. If $|K_1 - K_0|$ is within tolerance, the stationary equilibrium has been obtained. Otherwise, set $K_0 = \psi_K K_1 + (1 - \psi_K)K_0$ and return to step 1.

A.2.2 Transitions / impulse responses

We describe here the algorithm to compute a transition from one steady state (with equilibrium objects denoted x^*) to another (x^{**}). For an impulse response, of course, the assumption is that we eventually return to the initial steady state. We assume that the economy is in the original steady state in period 0, and that the shock hits in period 1. Note that since, in general, our shocks include shifts in the transition matrix over idiosyncratic states (in particular, the persistent component of earnings ϵ_2), there is an initial adjustment required to the distribution $\mu_1(x)$ to reflect the incidence of this shock.

1. Choose a number of periods T to reach the terminal steady state.

2. Compute the paths of exogenous shocks and states over this transition path.

3. Make initial guesses of the sequences of aggregate capital, $\mathcal{K}_0 = \{K_{0,t}\}_{t=1}^T$, and loan constraint multipliers, $\mathcal{A}_0 = \{\eta_{0,t}\}_{t=1}^T$.

4. Use these sequences to compute aggregate prices $\{r_t, w_t, i_t\}_{t=1}^T$.

5. Solve **backward** for the sequence of:

   (a) loan price schedules, $\mathcal{Q} = \{q_t(\ell; x)\}_{t=1}^T$. When computing period T prices, we use the fact that $g_{d,T+1}(\ell; x) = g_d^{**}(x)$.

   (b) value functions, $\mathcal{V} = \{V_t(x)\}_{t=1}^T$. We assume that $V_{T+1}(x) = V^{**}(x)$.

   (c) decision rules $\mathcal{G} = \{g_d(x), g_a(x)\}_{t=1}^T$.

6. Solve **forward** for the sequence of distributions over idiosyncratic states, $\mathcal{M} = \{\mu_t(x)\}_{t=1}^T$ by iterating on the T^* operator defined by equations (A.1) and (A.2) above. Note that we exploit the fact that $\mu_1(x)$ is known at the outset in this step.

7. For each period $t = 1, ..., T$, use the bisection described in step 7 of the steady state algorithm in order to compute an implied updated sequence of loan constraint multipliers $\mathcal{A}_1 = \{\eta_{1,t}\}_{t=1}^T$. If $\sup|\mathcal{A}_1 - \mathcal{A}_0|$ is within tolerance, proceed to step 8. Otherwise, set $\mathcal{A}_0 = \psi_\eta \mathcal{A}_1 + (1 - \psi_\eta)\mathcal{A}_0$ and return to step 4.

8. Use the sequence of distributions $\mathcal{M}$ to compute an implied sequence of aggregate capital stocks, $\mathcal{K}_1 = \{K_{1,t}\}_{t=1}^T$. If $\sup|\mathcal{K}_1 - \mathcal{K}_0|$ is within tolerance, the transition has been solved. Otherwise, set $\mathcal{K}_0 = \psi_K \mathcal{K}_1 + (1 - \psi_K)\mathcal{K}_0$ and return to step 4.

A.2.3 Stochastic equilibrium

The full business cycle version of our model builds on the algorithm of Krusell and Smith (1998). The key difference is that in each period of the simulation step ("outer loop"), we must use a bisection algorithm in order to solve for the equilibrium level of the loan constraint multiplier η. This involves solving for new decision rules at each date, which vastly increases the computational burden of the exercise relative to their original framework.

1. Form discrete grids over the **approximate** aggregate state $\hat{s} = \{K, N, z\}$, where K is aggregate capital, N is aggregate labor productivity, and z is TFP.

2. Guess parameters $\{\Phi_0(z)\}_{z\in\mathcal{Z}}$ of forecasting rules for the following set of model objects: tomorrow's aggregate capital K', tomorrow's aggregate labor productivity N', and the current return on savings $\bar{i} = 1/\bar{q}$:

$$\begin{aligned} \log K' &= \phi_K^0(z) + \phi_K^1(z)\log K + \phi_K^2(z)\log N && \text{(A.3)} \\ \log N' &= \phi_N^0(z,z') + \phi_N^1(z,z')\log N && \text{(A.4)} \\ \log(1+\bar{i}\quad) &= \phi_{\bar{i}}^0(z) + \phi_{\bar{i}}^1(z)\log K + \phi_{\bar{i}}^2(z)\log N + \phi_{\bar{i}}^3(z)\log K\cdot\log N && \text{(A.5)} \end{aligned}$$

3. Use the current parameters $\{\Phi_0(z)\}_{z\in\mathcal{Z}}$ to compute prices relevant for household decisions at each point on the approximate aggregate state grid:

   (a) **factor prices:** directly from (5) and (6);

   (b) **real interest rate:** steps 2a and 2b pin down an estimate of r' as a function of z', $\widehat{r'(z')}$, via (6) given the current approximate aggregate state. This further pins down a forecast of the current interest rate i, $\hat{i}$, via (18).

   (c) **savings price:** this is obtained direct from the forecast price, $\hat{\bar{q}} = 1/(1+\hat{\bar{i}})$.

   (d) **loan prices:** To obtain $\hat{\eta}$, we use the savings price condition (19) and the forecast $\hat{\bar{i}}$ from the step above:
   $$\hat{\eta} = \frac{1+\hat{\bar{i}}}{1+\hat{i}} - 1.$$
   Equation (20) then yields all loan price schedules directly.

4. Solve for the household value function and decision rules (using the same technique as step 4 in the steady state algorithm).

5. Use the default decision rule to compute an updated repayment probability function p_1 (using the same technique as step 5 in the steady state algorithm). If converged, proceed to step 6. Otherwise, update p_0 and return to step 3d.

6. Simulate a sample of length $T_0 + T_1$ periods. Use this sample to compute sequences of key aggregate variables, $\{K_t, N_t, z_t, K_t' = K_{t+1}, N_t' = N_{t+1}, \bar{i}_t\}_{t=1}^{T_0+T_1}$. The key complication in this step is that we must solve for the equilibrium η_t at each date, which involves re-solving decision rules at each date in the simulation, greatly increasing the computational burden of solving the model.

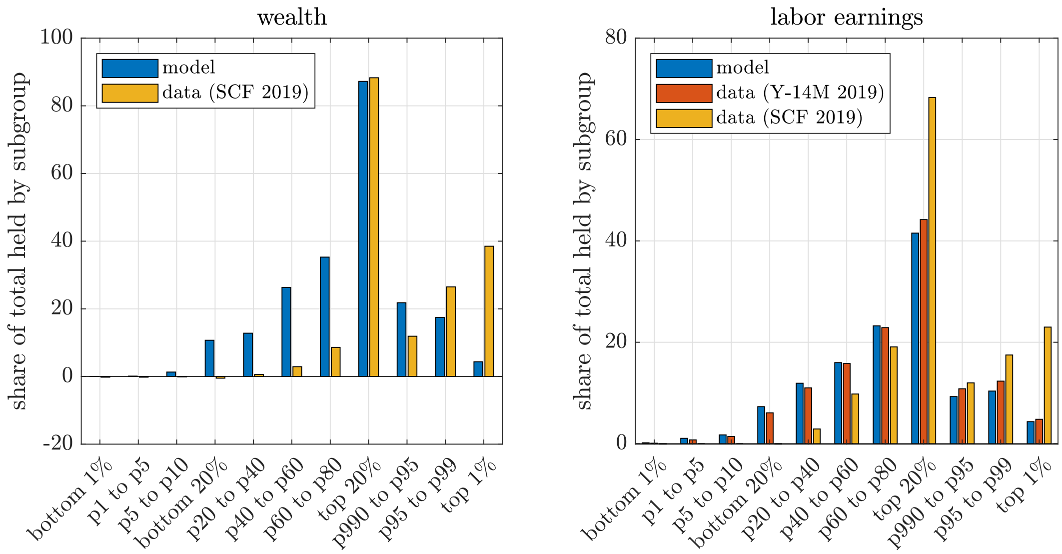


Figure A.1: **Distribution of wealth and labor earnings**

Notes: This figure reports the steady distributions of wealth and labor income in the baseline model and in the data (2016 SCF).

(a) begin with a sequence of aggregate shocks, $\{z_t\}_{t=1}^{T_0+T_1}$ (held constant across all iterations of the algorithm to insure consistency), and an initial distribution over idiosyncratic states $\mu_1(x)$. A sensible choice is the steady state distribution.

(b) for each date $t = 1, ..., T_0 + T_1$,

i. compute (K_t, N_t) implied by $\mu_t(x)$.

ii. use the procedure described in step 3 to obtain (interpolated) factor, savings, and loan prices, as well as an initial guess of the multiplier η_t^0.

iii. use interpolation on the aggregate state in order to compute the decision rules of the households from the inner loop described in steps 4 and 5.

iv. compute both sides of the loan supply constraint (17)

v. use step 7 of the steady state algorithm to solve for η_t.

A. if $|\eta_t^1 - \eta_t^0|$ is within tolerance, compute $\mu_{t+1}(x)$, factoring in the impact of z_{t+1} on earnings transitions.

B. otherwise, update η_t^0 via relaxation and recompute decision rules.

7. Use the simulated sample to update the forecasting rules $\{\Phi_0(z)\}$ by estimating equations (A.3), (A.4), and (A.5), omitting the first T_0 periods. If $\sup|\Phi_1 - \Phi_0|$ is within tolerance, then the model is solved. If not, set $\Phi_0 = \psi_\phi \Phi_1 + (1-\psi_\phi)\Phi_0$, where $\psi_\phi \in (0, 1]$ is a relaxation parameter, and return to step 3.

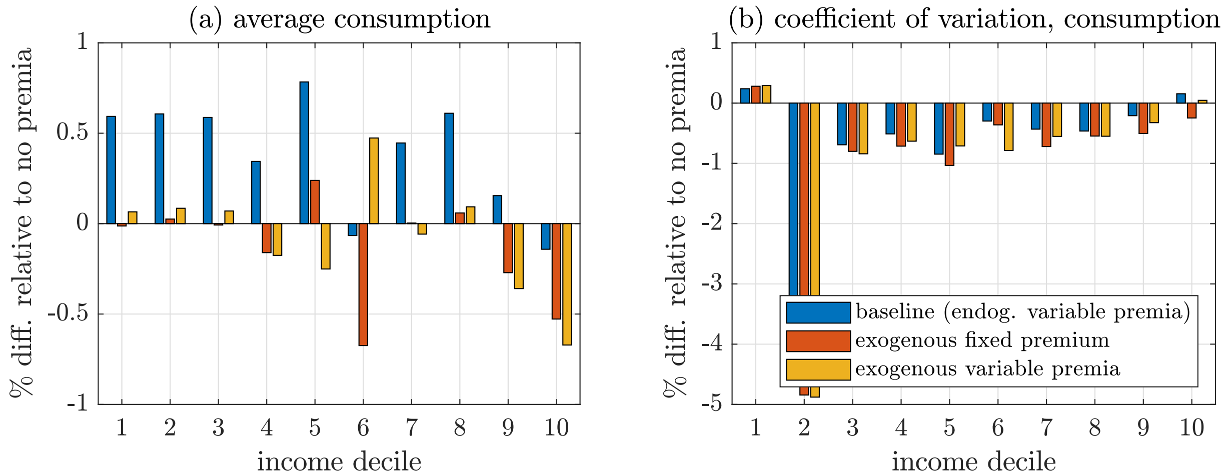


Figure A.2: **Consumption metrics in alternative economies**

A.3 Additional model and quantitative results

A.3.1 Equilibrium distributions of wealth and income

We compare our model's distributions of wealth and labor income to those in the data (SCF 2019 for wealth and income and Y-14M for income) in Figure A.1. While broadly replicating the shapes of these distributions, our model does not capture the extreme skewness or concentration at the top of the distribution in either metric. Notably, the model-implied distribution of income matches quite closely with that implied by Y-14M data.

A.3.2 Consumption across steady state model variants

Panels (a) and (b) of Figure A.2 show average consumption and its coefficient of variation (standard deviation normalized by mean), respectively, across the model variants considered in Section 5. The slight boost in average consumption across the distribution in our baseline model is attributed to the general equilibrium lift in return on savings; effects are more mixed in the two exogenous premia models we consider here. Panel (b) shows that borrowing premia lead to more volatile consumption for the poorest agents, but agents respond in (steady state) equilibrium by saving more for all income deciles above the bottom one.

A.3.3 Calibration and estimation results for impulse response exercise

Table A.3 and Figure A.4 lay out the parameters and model fit of our first dynamic exercise described in Section 6.1.1. The fit of the model to the schedule of borrowing premia estimated for the March - June 2020 period is summarized by the SSE in Table 4.

A.3.4 Calibration for business cycle model

Table A.1 presents the parameterization of the key aggregate-shock-dependent process for the stochastic equilibrium model described in Section 6.2. The TFP process is discretized into two states, with transition matrix $[1-\Gamma_{HL'}, \Gamma'_{HL}; \Gamma_{LH'}, 1-\Gamma_{LH'}]$, with $\Gamma_{LH'}$ parameterized

Parameter		Value	Notes
TFP process			
persistence	ρ_z	0.330	3-year recovery
TFP shock	Δ_z	-0.098	drop in GDP
earnings process			
persistence	ρ_ϵ	0.330	same as TFP
std. dev.,ϵ_2	$\sigma^R_{\epsilon_2}$	0.163	STY (2004)
lending standards			
persistence	ρ_λ	0.250	faster recovery
level	λ'_0	158.0	**See Fig. A.4**
location	λ'_1	-0.0047	
dispersion	λ'_2	0.0885	

Figure A.3: **Parameters for Covid shock exercise**

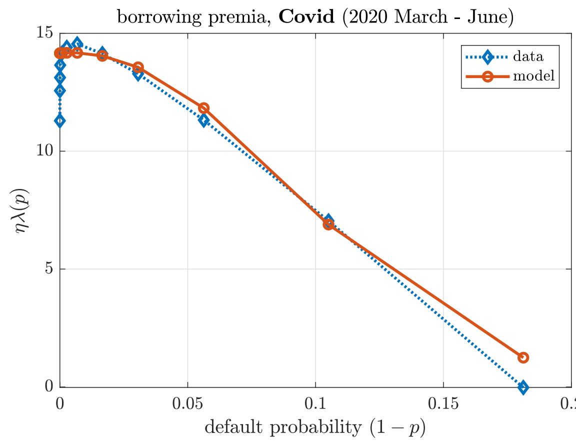


Figure A.4: **Model fit to empirical borrowing premia on impact of shock**

directly and $\Gamma_{HL'}$ determined given s_R and $\Gamma_{LH'}$. Both the earnings and lending standards process are tied directly to the realization of TFP, $z \in \{z_R = 0.9802, z_E = 1.0198\}$, for recessions and expansions, respectively.

A.3.5 Impulse response charts

Figure A.5 presents some additional results to those presented in Section 6.1. In addition to presenting the full impulse response paths (as opposed to only peak-to-trough differences), we report here several additional moments and model variants (in particular, the "fixed premium" cases we consider in steady state but drop for parsimony in later sections). Figure A.6 shows the distribution of welfare gains for the exercises in Section 6.1.

A.3.6 Forecasting rules for business cycle model

As described in Appendix A.2.3, solving the model with aggregate uncertainty involves forecasting the approximate aggregate state. The results of these forecasts are presented in Table A.2. Panel A shows the results for our baseline model with lending standards and endogenously determined borrowing premia, while Panel B shows the results for the version of the model with no premia. This former set of results contains an additional forecasting rule, designed as described above to allow households to forecast the crucial loan constraint multiplier η in order to compute prices for borrowing and saving. The results in Table A.2 show that households are able to (almost) perfectly forecast the parts of the approximate aggregate state required to compute equilibrium prices at each date and in each state. The overall standard errors of each forecasting regression are vanishingly small, and the (adjusted) R^2 of each regression exceeds 0.999.

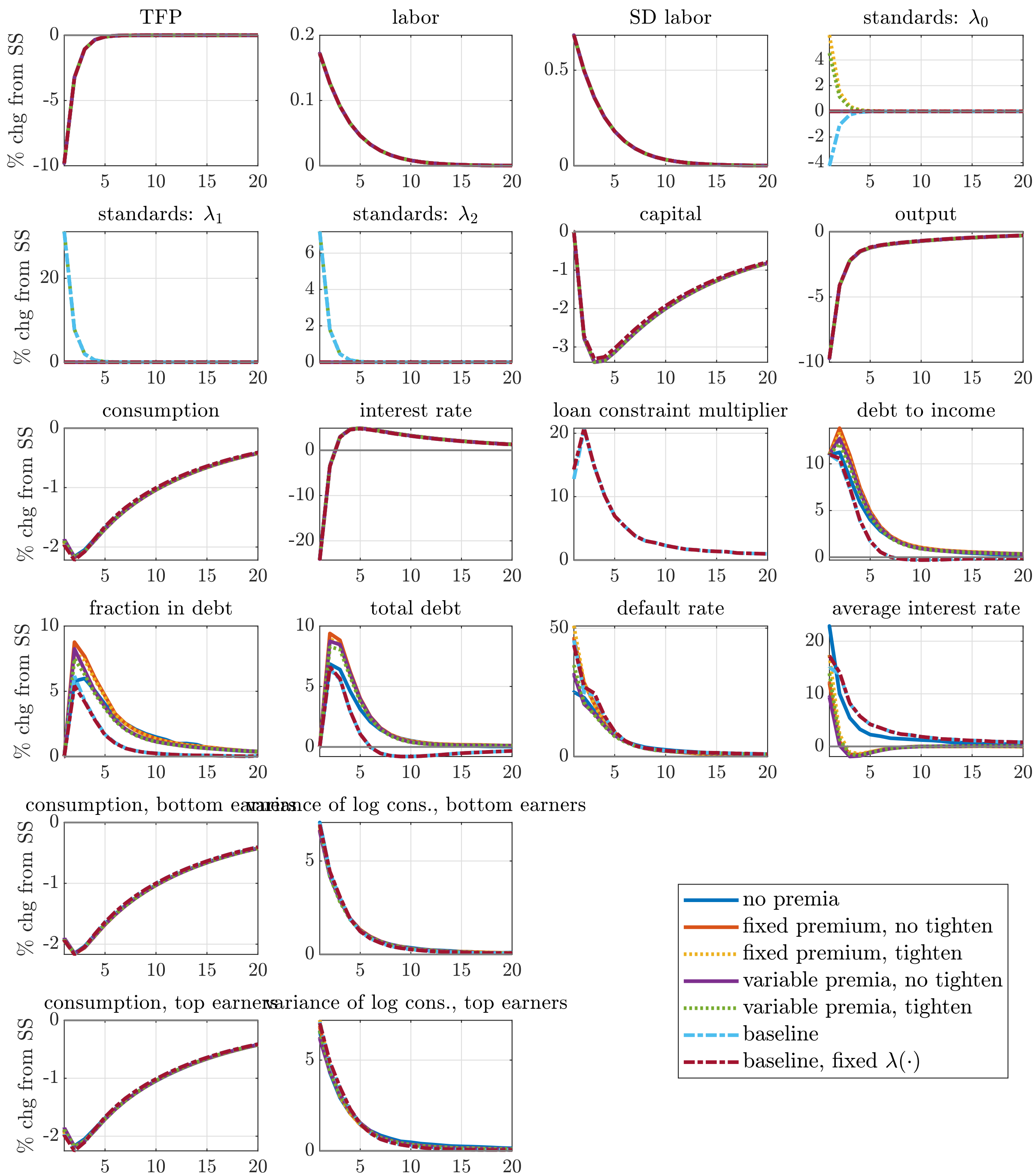


Figure A.5: **Covid shock responses**

Parameter		Value Rec.	Exp.	Target / Notes	Data	Model
TFP process						
TFP shifter	Δ_z	0.0198		standard deviation, GDP	1.20	1.20
share of low TFP	s_R	0.211		recession freq. (prob/yr)	0.21	0.21
low to high TFP prob	$\Gamma_{LH'}$	0.667		recession duration (yrs)	1.5	1.5
earnings process						
standard deviation, ϵ_2	σ_{ϵ_2}	0.163	0.094	Storesletten et al. (2004)		
lending standards						
level	λ_0	158.0	165.0			
location	λ_1	-0.0047	-0.0068	2019-20 borrowing premia		
dispersion	λ_2	0.0885	0.0826			

Table A.1: **Parameters calibrated for the full business cycle model**

Notes: The model period is annual. Earnings process and lending standards parameters take on the "recession" value when $z = z_R$ and the "expansion" value when $z = z_E$. Recession frequency and duration are expressed in annual and yearly terms, respectively.

B Data Appendix

In this Appendix section we describe in more detail the data sets we use, present several more findings and explain the equivalence between data and model moments.

B.1 Main data sources, sample construction, and additional facts

As described in Section 2, we combine two data sources to gain insights into credit terms and usage: (i) Y-14M, a detailed loan-level panel data set built from the portfolios of large bank holding companies in the United States, collected by the Federal Reserve Board as part of the Comprehensive Capital Analysis and Review; and (ii) the FRBNY Consumer Credit Panel (Equifax), a nationally representative five percent sample of all credit files for U.S. borrowers. This is feasible given that the population of borrowers in the two data sets is the same. Given the dominance of the largest banks in the credit card market, almost the entire universe of credit card loans and borrowers (as represented by Equifax) is in Y-14M.

Borrower credit risk We use as the common identifier borrower's credit risk type, as measured by the j^{th} vigintile (bin) of credit scores, $j = 1, ...20$. For our analysis, we use the proprietary credit score developed by Equifax ("Risk Score") and the FICO score available in Y-14M. The Risk Score has been used extensively in household finance research by academics and policymakers given its inclusion in the Equifax data set. The FICO score is the most commonly used credit score by lenders when providing and setting terms of credit. We map each vigintile of Risk Score in Equifax into its corresponding vigintile of FICO score in Y-14M. As argued in Section 2, this is reasonable because the two measures are equivalent in

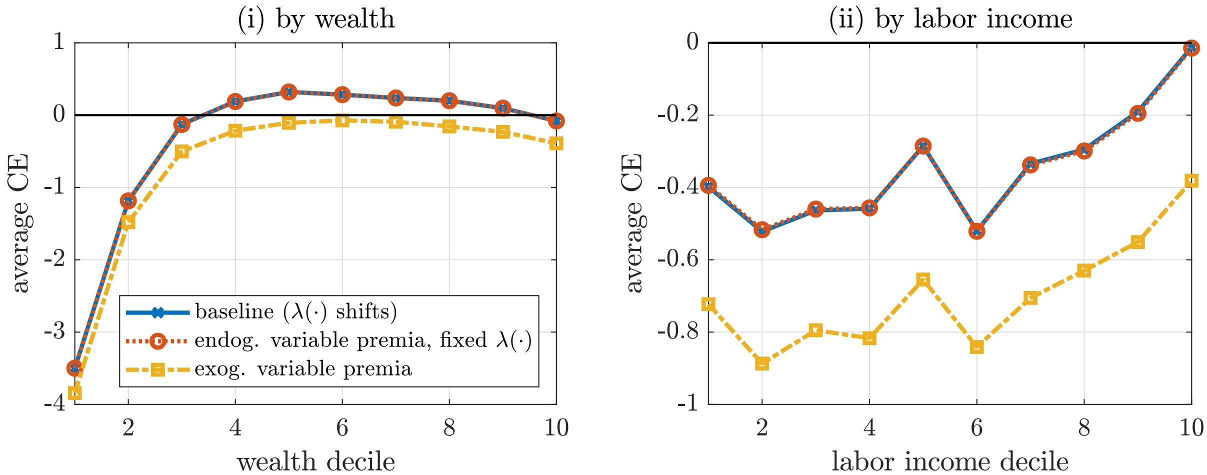


Figure A.6: **Covid shock: distribution of welfare by wealth and income**

Notes: Welfare is computed in consumption equivalent terms. Defining the value of an agent in state x in the "no premia" experiment on impact of the shock to be $\overline{V}_0(x)$, and the value of the same agent in alternative experiment i to be $V_{i0}(x)$, we compute $CE_i(x) = \left[\frac{V_{i0}(x)+A(\beta(x))}{\overline{V}_0(x)+A(\beta(x))}\right]^{1/(1-\gamma)} - 1$, where $A(\beta)$ is a term which adjusts for discount factor levels and transitions and risk preferences γ. We aggregate using the steady state distribution of agents in the no premia economy.

assessing likelihood of default. We provide further details on this here.

Both credit ratings integrate several common sources of information about consumers into a single score. Debt payment history is the most important determinant of one's credit score, but other factors matter as well: (i) levels of indebtedness; (ii) length of credit history; and (iii) credit limit utilization, among others. This information is collected by Credit Reporting Agencies (CRA) such as TransUnion, Experian, and Equifax in order to create detailed credit reports. Second, while numerous credit scoring models have been constructed in the past decades, they all use the CRA data to generate credit scores that can be queried by lenders and borrowers. Previous research has documented that these different credit scoring models provide largely similar information about the creditworthiness of consumers. For example, as the 2012 Consumer Financial Protection Bureau (CFPB) report shows, correlations across different credit scores are high (over 0.9), especially for consumers with lower credit scores. Authors calculations using CRISM data generate similar findings for the two scoring models we use in this paper.

Equifax We drop observations missing either risk scores or raw delinquency data. Given the low frequency of transactions for the three lowest risk score bins, we trim these bins from our sample. We compute narrow, baseline, broad default measures for borrowers with credit cards as follows:

1. **baseline:** bankruptcy or severe derogatory

2. **narrow:** bankruptcy only

3. **broad:** bankruptcy, severe derogatory, or 120 days past due

agg. state	z	z'	intercept	$\log K$	$\log N$	$\log K \times \log N$	R^2	s.e.	N
Panel A: Baseline model									
$\log K'$	z_H	-	0.236	0.877	0.000	-	0.9991	0.0002	1564
$\log K'$	z_L	-	0.117	0.923	0.138	-	1.0000	0.0000	436
$\log N'$	z_H	z_H	0.039	-	0.783	-	0.9998	0.0000	1280
$\log N'$	z_L	z_H	0.040	-	0.776	-	1.0000	0.0000	284
$\log N'$	z_H	z_L	0.074	-	0.610	-	0.9995	0.0000	284
$\log N'$	z_L	z_L	0.076	-	0.602	-	0.9999	0.0000	152
$\log R_S$	z_H	-	0.178	-0.068	0.000	0.001	0.9893	0.0000	1564
$\log R_S$	z_L	-	0.162	-0.062	0.023	0.000	0.9929	0.0000	436
Panel B: No premia model									
$\log K'$	z_H	-	0.231	0.879	0.000	-	0.9989	0.0002	1564
$\log K'$	z_L	-	0.107	0.928	0.129	-	1.0000	0.0000	436
$\log N'$	z_H	z_H	0.039	-	0.783	-	0.9998	0.0000	1280
$\log N'$	z_L	z_H	0.040	-	0.776	-	1.0000	0.0000	284
$\log N'$	z_H	z_L	0.074	-	0.610	-	0.9995	0.0000	284
$\log N'$	z_L	z_L	0.076	-	0.602	-	0.9999	0.0000	152

Table A.2: **Forecasting rules for model with aggregate uncertainty**

Notes: This table reports estimates and regression statistics for the forecasting equations (A.3), (A.4), and (A.5). Note for K' and i_S, there is a separate equation for each level of z, while for N' there is a separate equation for each z and z'. R^2 is the (adjusted) R^2 of the regression, and s.e. is the standard error of the regression. The last column presents the number of observations for each subsample of the total simulation of $T = T_1 + T_0 - T_0 = 2500 - 500 = 2000$ sample periods.

We use all four quarters in 2019 and compute the average probability of default for each credit score bin for this period. The baseline and broad definitions are quite similar, while the narrow measure preserves the pattern with a downward level shift (Figure B.1, right panel). When recomputing data moments for the Covid period, we keep our measure of probability of default unchanged since there is little difference in default probabilities across credit scores of borrowers between 2019 and March-June 2020 (Figure B.1, left panel).

Y-14M We construct our sample as follows. First, we take a 5 percent sub-sample and restrict attention to general purpose credit cards that are not securitized, secured or under promotion for accounts that are open (active or inactive) in each month. We focus on consumer bank cards which are general purpose credit cards, and we exclude non-consumer / business cards and private label / propriety cards, since these can only be used in the stores of the retailer issuing the card. We drop observations missing FICO score, APR, or end-of-cycle balance. Additionally, we drop observations for which: (i) the Vantage score is reported; (ii) FICO scores are below 300 or over 850; (iii) APR is below 5 percent. All these are very rate. We use the most recently updated credit score available for the primary account holder using a commercially available credit score unless it is missing, in which case we replace this with the credit score at origination. About 10% of the sample is replaced by

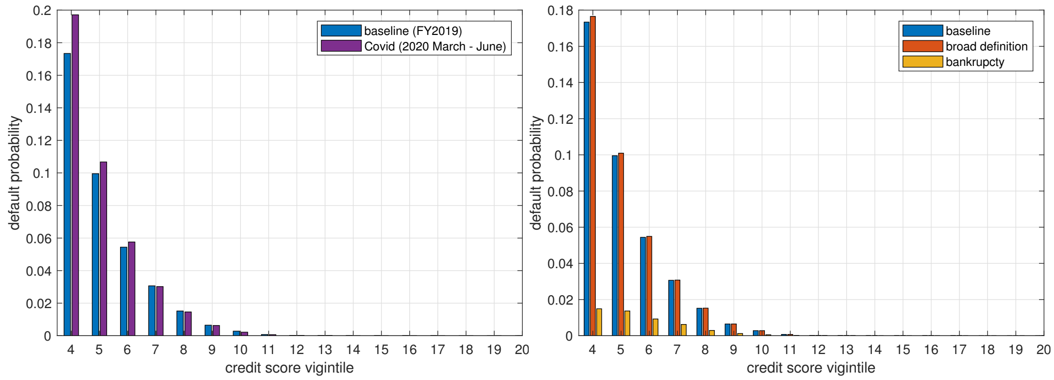


Figure B.1: **Probability of default across periods and alternative measures**

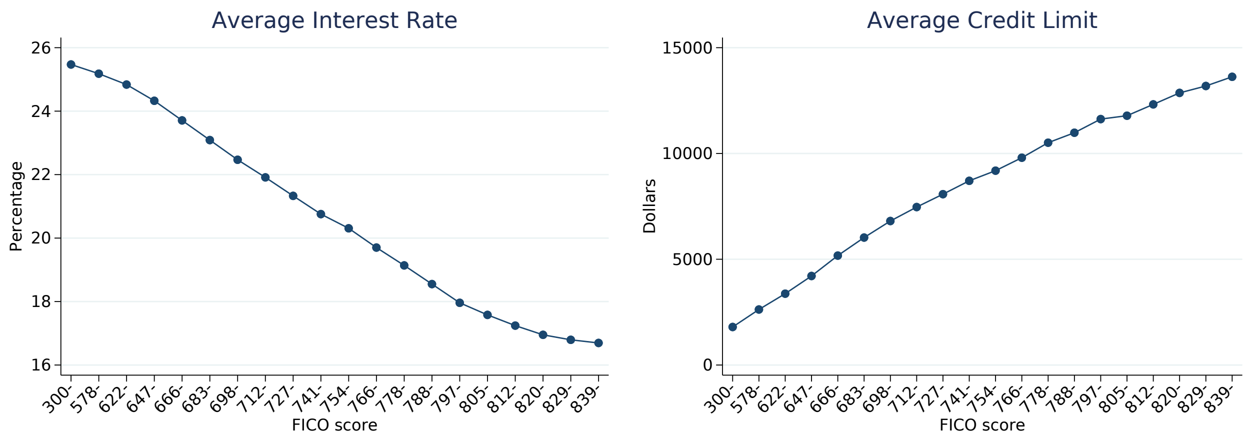


Figure B.2: **Interest rates and credit limits by FICO scores**

the score at origination.

Using this data set we compute for the 17 groups of credit type borrowers: (i) average interest rates (unconditional on debt and conditional on the population-wide median level of debt); (ii) average credit limits; (iii) share of total debt; (iv) average debt (unconditional and conditional on having a balance); and (v) debt to income. Again, we average over all 12 months of 2019. We compute the share of debt held by each bin as the ratio of the total balances in that bin to the total balances across all accounts. The construction of model moments is described in Section B.3. For robustness, we also compute these moments by income quartiles. Lastly, we recompute these objects for the March-June 2020 period.

For interest rates, we use the purchase APR for accounts that are not in default / workout, for which the default / workout APR is used. To average, we weight this APR by the total outstanding balance for the account at the end of each month's cycle. We also recompute this average interest rate conditional on observations with balances near the median level of debt (40th to 60th percentile). Aggregation is over FICO score bins and then over time. The left panel in Figure B.2 shows the interest rate schedule across bins. Note that figures here are reported in raw percentage points, not spreads as in the main text.

We compute similar patterns for credit card limits across FICO scores. We define the credit limit as the maximum dollar amount borrowers may take out on the account during the reporting month (reports are end of month). If there is no credit limit, banks report the purchase or shadow limit. We average over score bins then over time as for APRs described above, yielding the right panel in Figure B.2. Like APRs, credit limits vary greatly across borrower's risk, with tighter limits for low risk borrowers.

Moments conditional on income Additionally, we recompute interest rates and credit limits across credit scores also controlling for income and report findings in Figure B.3. The patterns in Figure B.2 are preserved when controlling for income. While borrowers with higher earnings generally face lower rates and higher credit limits, the differences across income groups are small. Unlike credit variables, income is self-reported. The data includes both income at origination and updated income at the end of the cycle for each month. While the latter variable is more desirable all else equal, it is not well populated and so we use the former. We restrict attention to accounts originated after 2005 to keep a reasonable level of informational value for borrowers' reported income. This trims only 7% of the sample and covers 90% percent of balances. We winsorize the income variable at 2% at the bottom and 1% at the top, and use CPI to convert income into 2019 dollars. For the remaining variables used for model validation in Section 4.3, we proceed in the same way. Lastly, we turn to the Covid crisis and recompute patterns using March-June 2020 in Y14M. Figure B.3b reports the schedules of interest rates and credit limits in the crisis period conditional on income. In general, interest rate schedules shifts upward and credit limit schedule downward across credit score and income groups, albeit by small margins.

B.2 Senior Loan Officer Opinion Survey (SLOOS)

B.2.1 Construction of diffusion indices

To construct an index for changes in standards and terms of credit we follow the methodology in Bassett et al. (2014) and use questions that ask participating banks to report whether they have changed their standards, or changed terms during the survey period.[59] Specifically, questions about changes in standards follow the general pattern of "Over the past three months, how have your bank's credit standards for approving credit card loans changed?" The possible answers, on a 1-5 scale, are:

1. eased considerably;
2. eased somewhat;
3. about unchanged;
4. tightened somewhat; and
5. tightened considerably.

[59] In constructing our indexes, we revisit the method used in Bassett et al. (2014) in two directions: first, we use more granular data by loan types when we compute the share for each loan category on banks balance sheet; second, when computing weights associated with each type of loan, we expand the universe of banks beyond respondents in the SLOOS in line with the Call Reports data.

(a) **Full year 2019**

(b) **Covid crisis: March - June 2020**

Figure B.3: **Interest rates and credit limits conditional on income**

Similar questions are asked for credit terms (interest rate spreads, credit limits), and the approach we describe below can be replicated for these specific terms as opposed to standards more broadly. Historically, SLOOS respondents rarely characterize their standards as having changed "considerably." Therefore, we collapse the scale as follows: $S_t^i = -1$, if bank i reported easing standards in quarter t, $S_t^i = 0$, if bank i left standards unchanged in quarter t, and $S_t^i = +1$ if bank i reported tightening standards in quarter t.

We weight a bank's responses by that bank's share of total consumer loans in the previous period ($w_{i,t-1}$) to obtain the aggregate measure of changes in lending standards, $\Delta S_t = \sum_i w_{i,t-1} S_t^i$. These weights are computed using the Call Reports. These indices reflect the net percent of consumer loans subject to tightened standards: positive (negative) values indicate eased (tightened) standards. We normalize these aggregate measures by their historical average to create an overall lending standards index, I_t^S, which measures standard deviations in each quarter t from its historical average. Figure 9 in the main text shows the index for lending standards for consumer loans, and Figure B.4 shows the indices for spreads and limits as well. The changes in standards for consumer loans and for credit card loans are

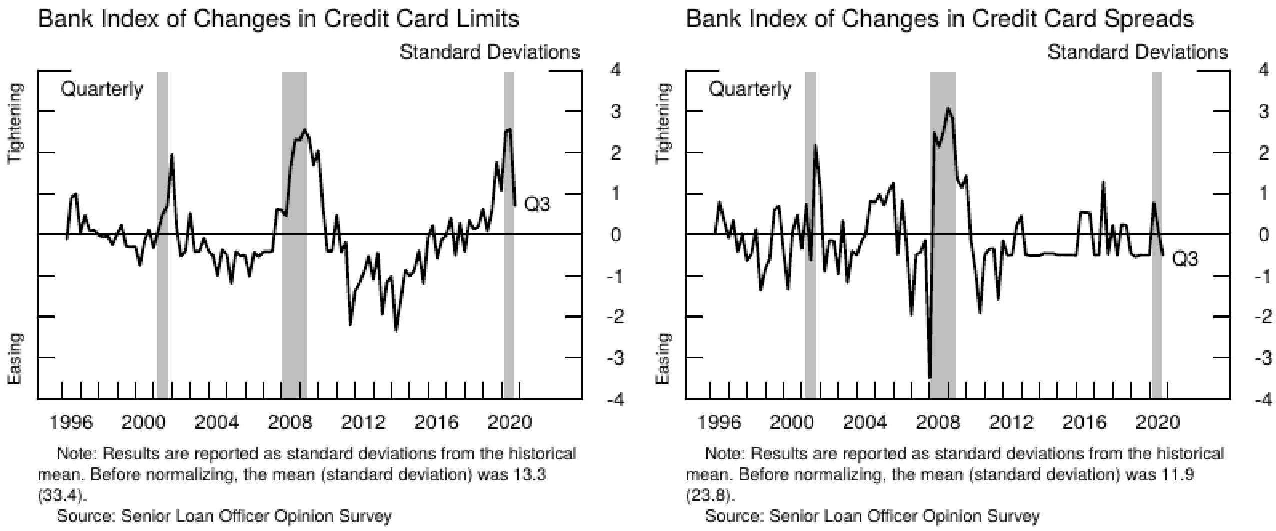


Figure B.4: **Lending standards for credit card loans**

quite similar, since credit card loans represent the largest category of loans included.

B.2.2 Additional survey evidence: special questions

In the October 2019 SLOOS, banks were asked about the reasons why they are less likely to approve credit card applications. As shown below, the most cited reasons were increased concerns about new borrower's ability to repay and deterioration or expected deterioration in the quality of loan portfolio as important reasons, with concerns more pronounced for high risk borrowers. Similar reasons were provided in previous years, with banks reporting that tightening of standards or terms were due to a deterioration or expected deterioration in the quality of their existing loan portfolio. In addition they also cited a less favorable or more uncertain economic outlook.

B.3 Moment definitions

In this section, we define key moments and metrics used throughout the paper, mainly model moments used in our model versus data comparison, that are not described in the main text. To ease notation, we express the individual state vector as x and describe a specific element of the state vector as a function of x. Except where necessary, we suppress explicit dependence on the time period t or the aggregate state s.

Macro moments The macro moments we use throughout the paper are standard. For business cycle moments, we take logs of the data and apply the HP filter with an annual smoothing parameter of 6.25. We use Equifax data for all credit quantities for which we present cyclical properties in Section 6.2, except for debt to income for which we use Y14M data. For interest rates on all credit card loans we use G19 data and for interest rates on risk free loans we use Y14M data. We use 1999-2019 for series constructed from Equifax and G19, given that 1999 is the first year available in Equifax, whereas for series constructed from the Y14M data, we start only in 2014, the first year available.

Fraction in debt, volume of debt, and share of total debt We define the fraction of agents in debt to be the fraction of agents with negative net worth, $a < 0$. For a given period t, this fraction is $\sum_x \mu(x)\mathbf{1}[a(x) < 0]$. The total volume of debt is: $-\sum_x \mu(x)a(x)\mathbf{1}[a(x) < 0]$. The share of total debt accounted for by a subgroup applies the above metric to the subgroup, then weights by the total. In the data, we compute this fraction in Equifax as the fraction of consumers that hold positive credit card debt. In the data, we define credit as the total credit card debt balances in Equifax, excluding bankruptcy, the exact counterpart of our model. Recall that in the event of a bankruptcy, the household cannot borrow or save in the current period. Alternatively, one can use Total Real Revolving Consumer Credit Outstanding from the Flow of Funds/G.19 data, Federal Reserve Board (FRB)), case in which credit cannot be adjusted for bankruptcy at the individual level as Equifax data allow us to do. If the stock of revolving credit is adjusted using the credit card bankruptcy or charge-off rate, the correlation with GDP is negative, otherwise it is positive. Furthermore, while the large volatility is robust relative to the time periods used, this is not the case for the correlation. For instance, in the subperiod 1980-2018 the correlation is 0.33 as noted by Nakajima and Rios-Rull (2019). Fieldhouse et al. (2016) point out that over the 1993-2006 period, such correlation was negative. In line with our paper, they also point out that this correlation is even more negative when adjusted for charge-offs.

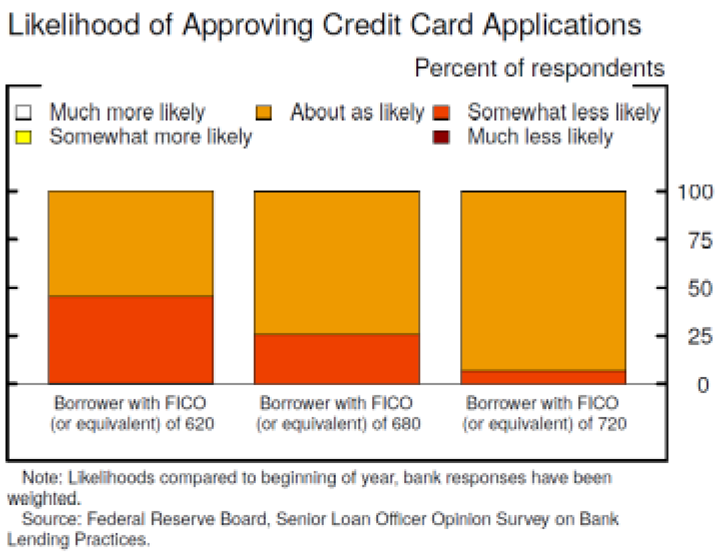
Debt to income ratio We compute the debt to income ratio conditional on borrowing: the ratio of an agent's total debt ($a\mathbf{1}[a < 0]$) divided by total labor income ($w\epsilon_1\epsilon_2\epsilon_3$). We normalize by the fraction in debt, defined above. In the data, we use Y14M data at the account level on credit card debt outstanding at the end of balance and income at origination (recall that income at the end of balance is an optional reporting variable in the data and quite sparse and so we are limited to using income at origination). Although imperfect, given that income is highly persistent we believe that the properties of this series represent a reasonable proxy for current debt to income measure.

Bankruptcy rate The bankruptcy rate is $\sum_x g_d(x)\mu(x)$. To compute a conditional metric (either on being in debt or by income group), we normalize the distribution by the desired population. In the data, we use the exact same definition of default rate from Equifax used for default probability in the model as described in Section 2 (bankruptcy and severe derogatory) as well as using only the bankruptcy flag in these data to compute cyclical properties for default and bankruptcy rates in Section 6. Constructed variables in this way are based on the universe of consumers modeled in our paper. Alternatively, one can use the number of bankruptcies (obtained from U.S. Courts) normalized by the number of households (from the Census), as in Nakajima and Rios-Rull (2019), with properties of these objects presenting similar patterns. In particular, bankruptcy filings are also highly volatile and countercyclical. Specifically, they find that for all bankruptcies relative volatility is 8.5 and correlation with GDP is -0.47.

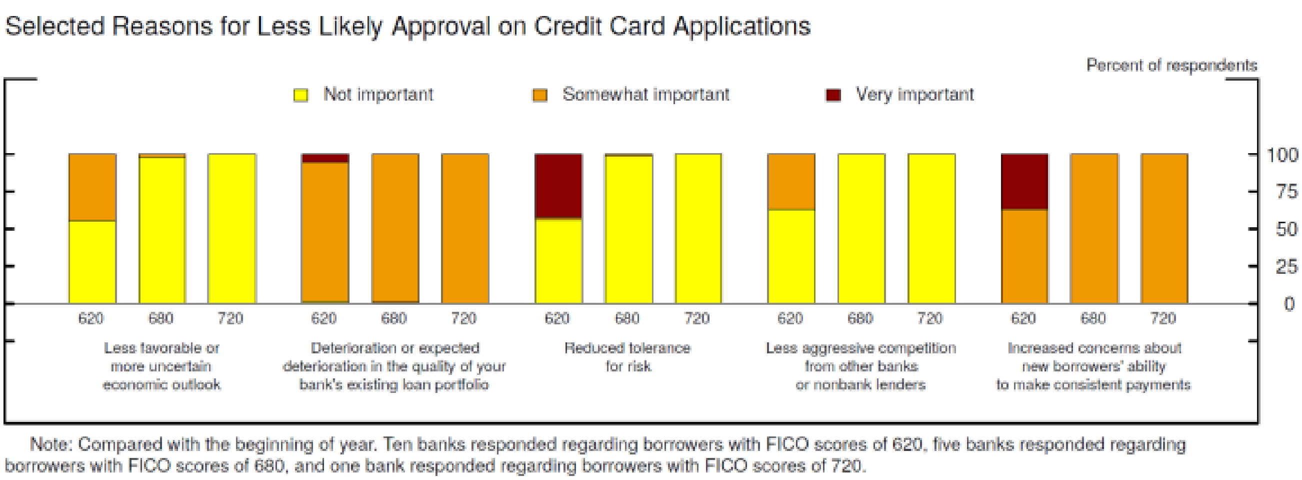
Average interest rate We compute the loan-weighted average interest rate conditional on borrowing as

$$\sum_x \mathbf{1}[g_a(x) < 0] \left(q^{-1}(g_a(x); x) - 1\right) \mu(x) / \sum_x \mathbf{1}[g_a(x) < 0]\mu(x)$$

In steady state, the denominator is equal to the (constant) fraction in debt, but this is not in general true when aggregate shocks are present in the environment. For business cycle calculations, we use G19 data from FRB for interest rates of all credit card accounts which we adjust for the federal funds rate. There is another interest rate of credit card debt that is available that is associated with credit card accounts assessing interest. It turns out, however, that the business cycle properties of both series are almost identical so we do not report them. For risk-free loans, we use Y-14M data for interest rates of all credit card accounts of super-prime borrowers for which default rate is 0 conditional on median debt level. This corresponds to the 12 vigintiles of FICO scores above 750. As in the case of the interest rate on all loans, we adjust for the federal funds rate.



(a) **Changes in lending standards by credit scores**



(b) **Reasons for tightening credit by credit scores**

Figure B.5: **Additional survey evidence from SLOOS**